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BDA 640: Data-Driven Decision Making and Optimization Section

Enhancing Hospital Observation Unit Performance Analysis

1. Executive Summary

The project aimed to enhance the operational efficiency of the Observation Unit (OU) at Montanaro Hospital, located in a medium-sized U.S. city. It addressed challenges associated with patient placement and the efficiency of the OU's exclusion list. The initiative was driven by concerns over the prolonged average duration of patient stays and the frequent reclassification of cases from observation to inpatient status. To address these issues, a data-driven approach was adopted, involving the examination of historical patient data to formulate a predictive model. This model was intended to improve the accuracy in identifying patients suitable for the OU, thereby optimizing patient flow and unit efficiency. After comprehensively comparing three models, including logistic regression, classification tree, and random forest, the classification tree emerged as the best predictive model. When applied to the initial intake practice in the Observation Unit (OU), it effectively reduced the flipped rate to one-third. This reduction implies that the OU can potentially accommodate five additional patients per week and effectively reduce the average length of stay for patients in the OU. Furthermore, due to the interpretability of the classification tree, it was possible to create decision rules. Consequently, according to the models' findings, it's recommended that conditions involving dehydration, congestive heart failure, pneumonia, colitis, pancreatitis, gastrointestinal bleeding, and urinary tract infection should be added to the Montanaro OU exclusion list. To further enhance the efficient strategic operations of the OU, the Chief of Medicine should create standardized clinical pathways and protocols, set Key Performance Indicators (KPIs) for performance evaluation, improve care coordination through interdisciplinary meetings, and implement a strategic bed management system for optimal patient placement.

2. Problem Description

The case description highlights critical issues regarding the inefficiency of the operational management of the Observation Unit (OU). It centers on concerns about the average length of stay for patients in the OU and the substantial number of patients transitioning from observation to inpatient status. Due to the high patient volume in the OU, there is a shortage of bed capacity, resulting in, on average, observation-level patients being placed in inpatient beds. The transfer of patients between inpatient wards and the OU is considered to be a waste of hospital resources, increasing overall patient length of stay and elevating the risk of medical errors during handoffs. This issue underscores the need to refine the OU exclusion list and optimize the use of the hospital's Observation Unit by predicting which patients are likely to transition from observation to inpatient status. Addressing these issues is crucial for improving patient care management and enhancing operational efficiency by ensuring that only the most appropriate patients are transferred to the Observation Unit.

3. Methodology

3.1 Data Collection, Cleaning, and Preprocessing

The data used in this study were collected from Montanaro Hospital's Observation Unit, which has 1,111 patient records with 15 variables. In this section, we will navigate through the process of data exploration, cleaning, and reprocessing, which involves thoroughly examining the dataset for inconsistencies, missing values, outliers, and variable types. This ensures that the study data is primed for accurate analysis and modeling.

(1) *Dimension and Characteristics of the Dataset*

Upon examining the data types for an initial overview, it was discovered that some variables in the dataset require conversion to different data types to align with their intended analytical function and ensure accurate modeling.

(2) ***Type Conversion and Binary Encoding***
The variables for systolic blood pressure, diastolic blood pressure, pulse, and other related measures were converted into numerical types. Additionally, the two categories of the 'Gender' variable, Male and Female, were coded as 1 and 0, respectively. 'DRG01 (Initial Diagnosis-related Group)' was transformed into a categorical variable. During this process, issues arose with converting 'Blood Pressure Diff,' and further investigation through summary statistics revealed numerous missing values. The next step is to identify and address these special or erroneous values.

(3) ***Identify Potential Errors, Missing Values of the Dataset***
Twenty records containing missing values were identified: 3 in the variable BloodPressureUpper, 4 in BloodPressureDiff, 4 in Pulse, 1 in PulseOximetry, 4 in Respirations, and 4 in Temperature. Missing values marked as '#VALUE!' are converted to 'NA' for further processing, such as in the variable 'BloodPressureDiff'.

(**4)** ***Handling Missing Values and Inconsistent Data***
The dataset comprises 1,111 observations with a relatively small number of missing values. Imputing the missing values is the most appropriate method, ensuring the retention of as much data as possible, crucial for constructing an accurate predictive model. Since the variables with missing values, such as blood pressure, pulse, and temperature, are continuous, using the median for each variable is recommended to fill in the missing values. The median is less sensitive to outliers, making it well-suited for medical data. Given that the dataset defines 'BloodPressureDiff' as representing the difference between systolic and diastolic blood pressures, and upon examination, errors are identified in its difference, and it becomes necessary to recalculate this variable for the entire dataset.

(5) ***Identify Potential Errors and Inconsistencies in Categorical Variables***
Figures 1 to 5 display that after creating bar charts to examine potential category inconsistencies within categorical variables, no inconsistencies were found in the dataset.

(6) Inspecting Numeric Variables for Outliers
Box plots were generated to visually inspect numeric variables for outliers. According to Figures 6 to 14, outliers were observed in all numeric variables except for the 'Age' variable. However, given that these data originate from patients in the hospital's Observation Unit, such outliers may not significantly impact this study's analysis. Instead, they could indicate critical clinical cases or rare health scenarios that are important for the predictive model.

3.2 Data Visualization Description
Bar charts are used to show the distribution of categories or proportions, providing deeper insights into the relationships between variables, trends, patterns, and potentially hidden insights within the dataset. Figures 16 to 18 reveal that the data used in this study includes records of two groups: non-flipped and flipped. Patients admitted to the Observation Unit (OU) range from 19 to 89 years old. The rate of males admitted to the OU and flipped from observation to inpatient status is slightly higher compared to females. There are five different types of insurance: private insurance plans, Medicare, Other Medicare, Medicaid, and Other Medicaid. Regarding the primary insurance category, Medicare insurance has the highest proportion of cases flipped to inpatient, with private insurance being the lowest, and the other three categories showing minor differences. Additionally, there are twelve different diagnosis groups in the data used for analysis, and their rates between flipped and non-flipped patients differ. The proportions for pancreatitis, colitis, and urinary tract infection rank as the 1st, 2nd, and 3rd diagnoses with the most patients coming to the OU, respectively, while abdominal pain has the lowest proportion.

Figures 15, 19 to 28 indicate that the average values of the variables, including 'Age,' 'Flipped,' 'BloodPressureUpper,' 'BloodPressureLower,' 'BloodPressureDiff,' 'Pulse,' 'PulseOximetry,' 'Respirations,' and 'Temperature,' show little difference between the two categories of cases flipped to inpatient and not flipped to inpatient, except for 'OU_LOS_hrs.

The correlation coefficients between variables are calculated to better capture the relationships and explore the potential for multicollinearity. Table 1 shows that the Primary Insurance Category and the initial primary diagnosis (DRG01) have a moderate correlation with the flipped status from observation to inpatient, suggesting that these factors play a significant role in determining whether a patient is flipped to inpatient status. Other variables, such as Gender and numerical variables representing the patient's physiological parameters, for example Pulse, PulseOximetry, Respirations, and Temperature, exhibit lower correlations with the flipped status, indicating a less direct impact. There are a few blood pressure-related metrics that show high correlations with each other, highlighting the interconnectedness of these physiological measures.

3.3 Variable Selection and Model Used

The variable 'OU_Los_hrs' represents the length of patients' stay in the Observation Unit (OU). The OU is currently struggling to identify patients because it is overcrowded, and the hours do not correctly reflect the situation. It might be challenging to rely solely on this variable for accurate predictions, as the duration of stay is not initially known when predicting new observation cases. Including the length of patient stay in the OU as a variable could lead the model to predict based on outcomes rather than the underlying reasons for hospital admission. The model should focus on variables observable at the onset of the patient's visit to make accurate predictions. Furthermore, from the analysis of the relationships between variables, it is observed that 'BloodPressureDiff' is highly correlated with 'BloodPressureUpper.' The inclusion of both variables in predictive models should be evaluated for multicollinearity. Thus, the stepwise method is used to find the best model.

Data analysis and machine learning algorithms can address the challenge of predicting which patients will transition from observation to inpatient status. By utilizing historical patient data, it's possible to develop predictive models that evaluate the likelihood of a patient eventually requiring inpatient care. Machine learning algorithms, including logistic regression, decision trees, and random forests, can be utilized to forecast patient outcomes with significant accuracy. These models can sift through data to uncover patterns and correlations that signal key factors influencing a patient's shift from observation to inpatient status. The deployment of these models enables healthcare providers to make more informed decisions regarding patient placement. When assessing the performance of machine learning models applied to predicting patient outcomes in Observation Units (OU), it's essential to evaluate their effectiveness not only through traditional metrics such as accuracy, sensitivity, specificity, and Area Under the Curve (AUC) but also by examining metrics specific to the healthcare context. These context-specific metrics are crucial for a comprehensive evaluation, and they include:

- *Flipped Rate*: This rate measures the percentage of cases where patients initially placed in observation status are later changed to inpatient status.
- *Inpatient Mismatch Rate*: This metric refers to the proportion of patients who are incorrectly placed in inpatient wards when they should have been kept in observation units (OU).
- *Number of Treated Patients per Week*: This metric quantifies the total number of patients treated within a week, serving as an indicator of the model's efficiency in managing patient flow.
- *Average Length of Stay (LOS) per Patient*: This measure calculates the average duration that patients spend in the hospital.

4. Results

4.1 Model Predictive Performance Analysis

Table 2 presents the findings of the predictive models built using logistic regression, classification tree, and random forest. It is observed that all three models display similar accuracy, indicating their comparable ability to predict both positive and negative cases in the test dataset. However, in terms of specificity, the measurement of the model's ability to correctly identify patients who do not require hospitalization, which is denoted as the negative class, the classification tree model outperforms the others with a specificity of 0.6653. This suggests that the classification tree is more accurate in classifying patients fit for the Observation Unit compared to those requiring inpatient care. Additionally, the classification tree appears to offer a more balanced capability in identifying positive and negative classes.

According to the ROC curve and Lift chart, as shown in Figures 35 and 36, it is evident that the predictive capabilities of the Logistic Regression, Classification Tree, and Random Forest models are relatively close to each other. Specifically, the AUC values on the ROC curve are within a narrow range: Logistic Regression leads slightly with an AUC of 0.6758, Random Forest follows closely at 0.6625, and Classification Tree is not far behind with an AUC of 0.6496. This indicates that while Logistic Regression might be marginally better at discriminating between the patient outcomes, the difference in performance among the three models is not substantial. The Lift chart reinforces this observation, showing that all three models perform better than random chance at identifying true positives, and their curves are clustered across the number of cases. This implies that each model would likely provide a comparable lift in identifying patients who require inpatient care over random selection.

4.2 Model Application and Assessment

In evaluating the performance of machine learning models for predicting patient outcomes in Observation Units (OU), the focus is on a test dataset derived from a cleaned dataset, consisting of 445 observations. Within this dataset, 204 cases, or approximately 45%, were identified as " Flipped=1", indicating these patients ideally should have been recognized early on for inpatient care rather than being placed in the OU initially.

Assuming the use of the predictive model is to identify among these 445 patients those likely to require direct inpatient care. The results from a decision tree predictive model are considered as an example. According to the model's confusion matrix, it correctly predicted 125 patients needing hospitalization; however, it failed to identify another 79 patients who would be left in the OU but eventually required a transition to inpatient status. Additionally, the model accurately identified 157 patients as appropriate for care in the OU but incorrectly suggested that 84 patients who were actually fit for OU be admitted to inpatient beds. The application of the decision tree model resulted in a situation where, out of the 236 total patients left in the observation unit, 79 patients would be flipped, translating to a flipped rate of 33.5%. This implementation suggests a significant reduction in the percentage of patients whose status was changed to inpatient, effectively lowering it to about one-third. Consequently, with a flipped rate of one-third, this model would enable the OU to treat an average of 49 patients every week, potentially accommodating an additional 260 patients annually. However, it also means that 34.85% of patients who were appropriate for OU care would be inaccurately placed in inpatient beds. An analysis of the 236 patients managed in the OU under this model reveals an average length of patients' stay (LOS) in the OU of about 53.64 hours.

After applying three different models to the test dataset, the results presented in Table 3 indicate that the classification tree model outperforms the others in terms of the flipped rate, the number of patients treated per week, and the average length of stay per patient. Consequently, considering the overall performance across these key metrics, the classification tree emerges as a superior model for practical application. It demonstrates a better balance in accurately predicting patient outcomes, efficiently managing patient flow, and minimizing the length of hospital stays, making it a more effective tool for use in observation units.

4.3 Revenue Optimization Model

An optimization model is employed in this study to analyze revenue insights for OU performance. Drawing from typical hospital scenarios, it is assumed that the reimbursement rates of insurance, including Private, Medicare, Medicare Other, Medicaid, and Medicaid Other, are at different rates. In addition, inpatient care will cost more than observation-level care due to more extensive services. Table 4 displays the average insurance reimbursement prices for the observation unit and inpatient unit.

Due to the high patient volume in the OU, it is assumed that the OU's utilization by medical providers is around 90%. The OU targets include reducing the percentage of flipped patients from 45% to 20% and treating 55 patients per week in the OU instead of 44 patients. Therefore, it is assumed that weekly OU patient admission numbers range from 8 to 11.

Combining the prices and admission range data, Excel's Solver function is used to find the optimal flipped rate that can maximize daily revenue for the hospital. Furthermore, when comparing the OU revenue obtained from the optimization model with the OU revenue generated by the current OU flipped rate and the classification tree model, the results show that the classification tree model can align with achieving the same OU revenue as the optimization model; however, the classification tree model demonstrates a significantly greater reduction in the flipped rate, as illustrated in Table 5.

5. Recommendation

To address and improve the operational challenges and inefficiencies in the observational unit (OU), including reducing the high flipped rate and average length of patient stays in the OU, we have five recommendations, and they include:

(1) *Refinement of OU Exclusion List:* Analysis using advanced models has identified "DRG01" as a significant predictor for patient transition to inpatient status, pinpointing conditions like dehydration, congestive heart failure, pneumonia, colitis, pancreatitis, gastrointestinal bleeding, and urinary tract infections as key. These conditions, with a flipped rate over 50%, are recommended for inclusion in the OU Exclusion List.

(2) *Clinical Pathways and Protocols:* To enhance patient care efficiency, it is recommended to establish, develop, and implement standardized clinical pathways and protocols for common conditions leading to OU admissions. Additionally, continuously updating the Exclusion Diagnosis List is crucial.

(3) *Performance Metrics Monitoring:* Key performance indicators related to OU performance, including flipped rates, average length of stay, and patient satisfaction, will be established, regularly monitored, and use the data for continuous improvement.

(4) *Care Coordination:* Care coordination is crucial, especially in a hospital environment. Efficient communication and teamwork among healthcare providers, nurses, and support staff are essential to enhance the coordination of care. Moreover, conducting regular interdisciplinary meetings can assist in planning and addressing patient needs.

(5) *Bed Management:* An effective bed management system will be utilized to allocate beds based on patient acuity and urgency, helping prevent bottlenecks and ensuring that patients are promptly placed in appropriate beds.

Reference

1.Dessislava Pachamanova, Vera Tilson, Keely Dwyer-Matzky (2021) Case Article—Machine Learning, Ethics, and Change Management: A Data-Driven Approach to Improving Hospital Observation Unit Operations. INFORMS Transactions on Education 22(3):178-187.

Appendix

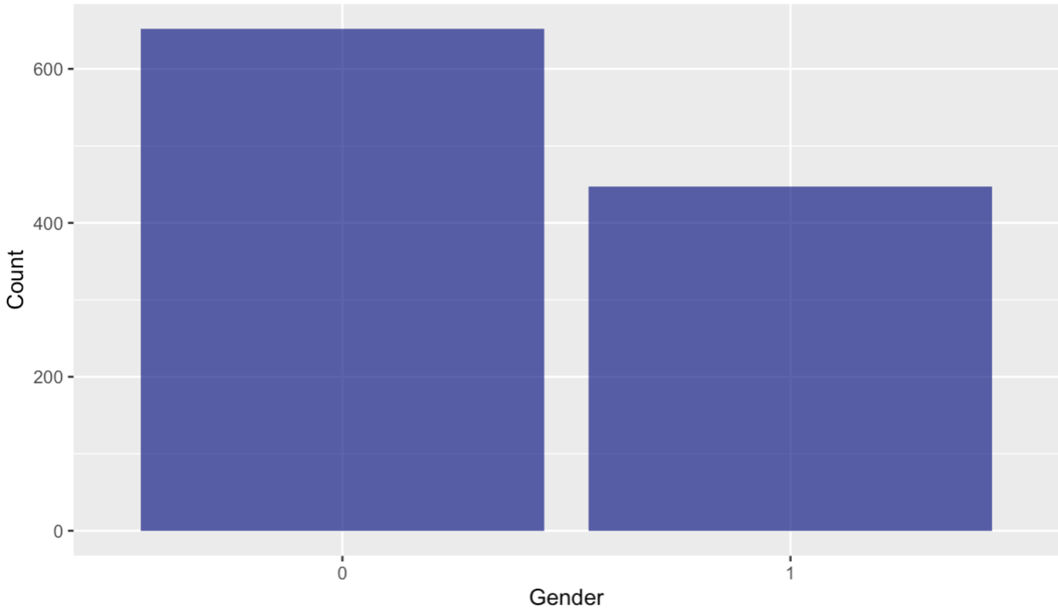

Figure 1. Barplot of Gender

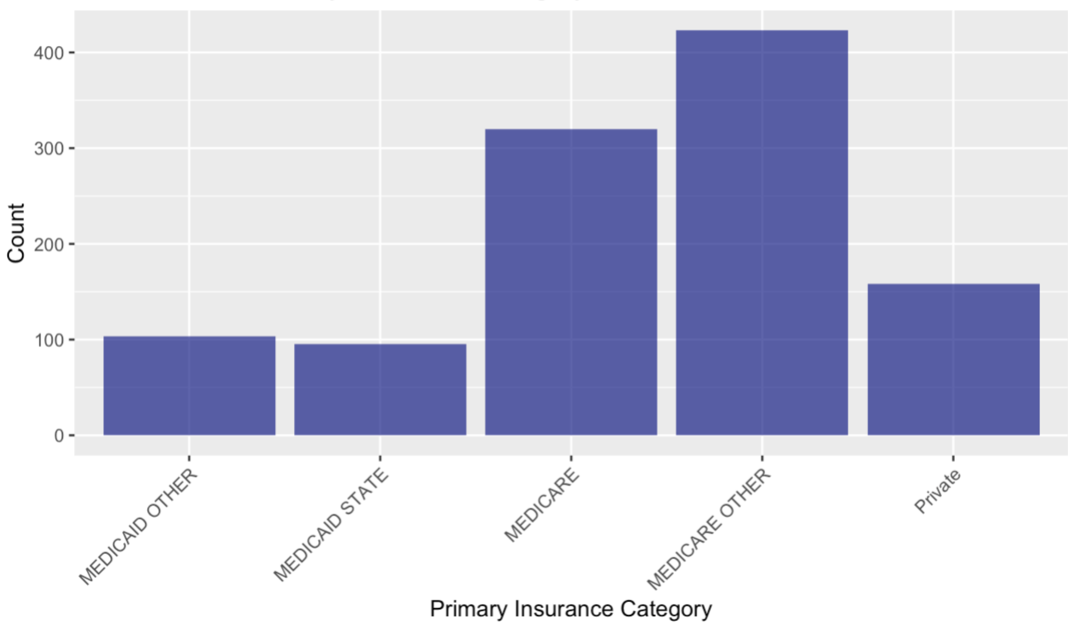

Figure 2. Barplot of Primary Insurance Category

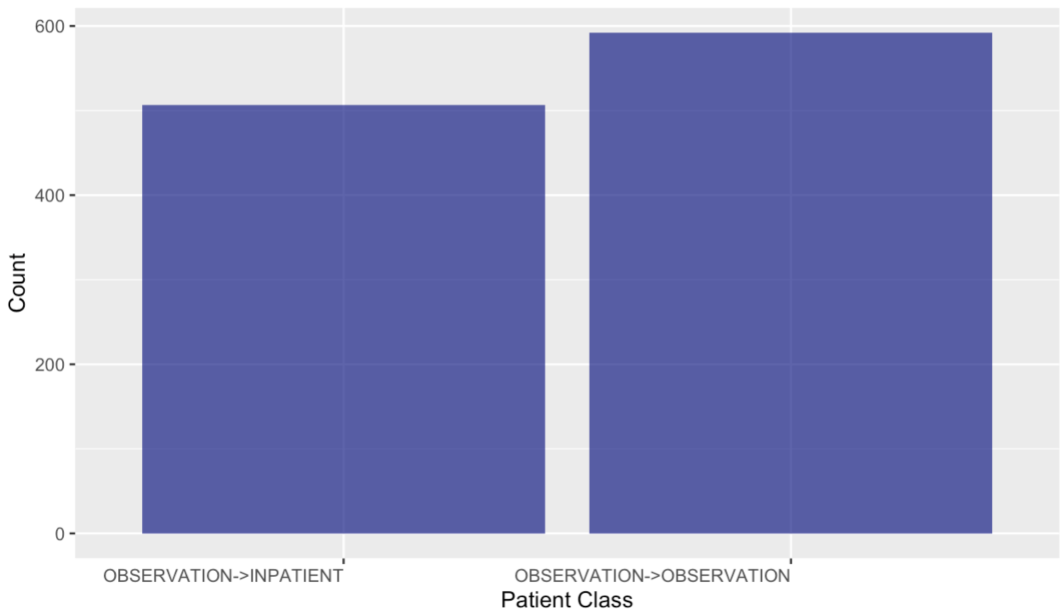

Figure 3. Barplot of Patient Class and First Post OU Class

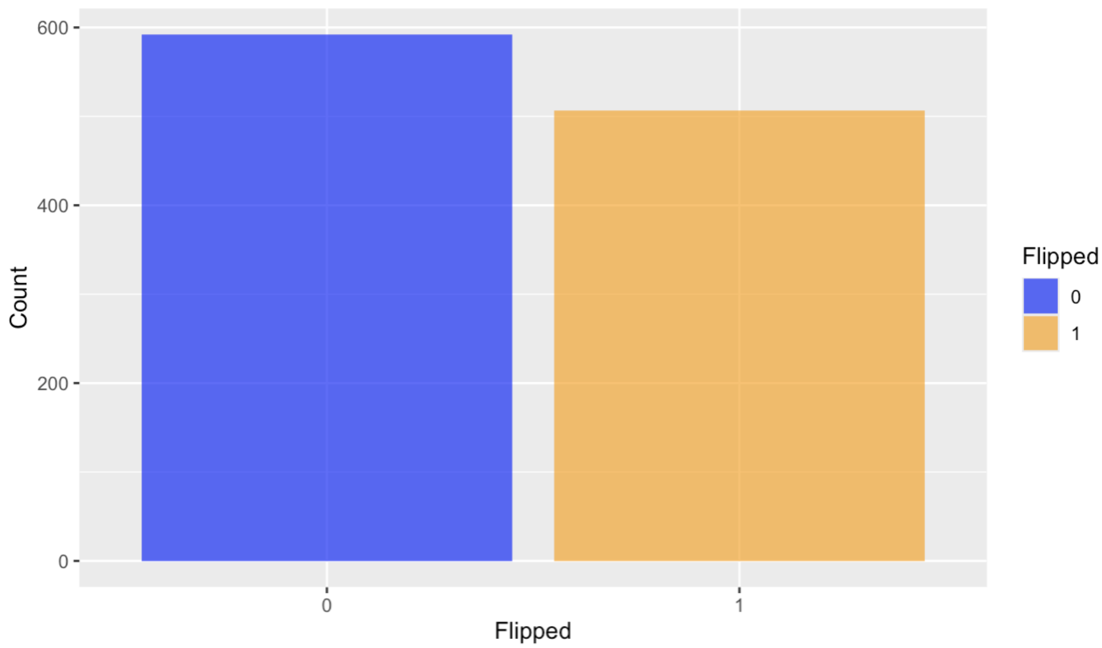

Figure 4. Barplot of Flipped Status

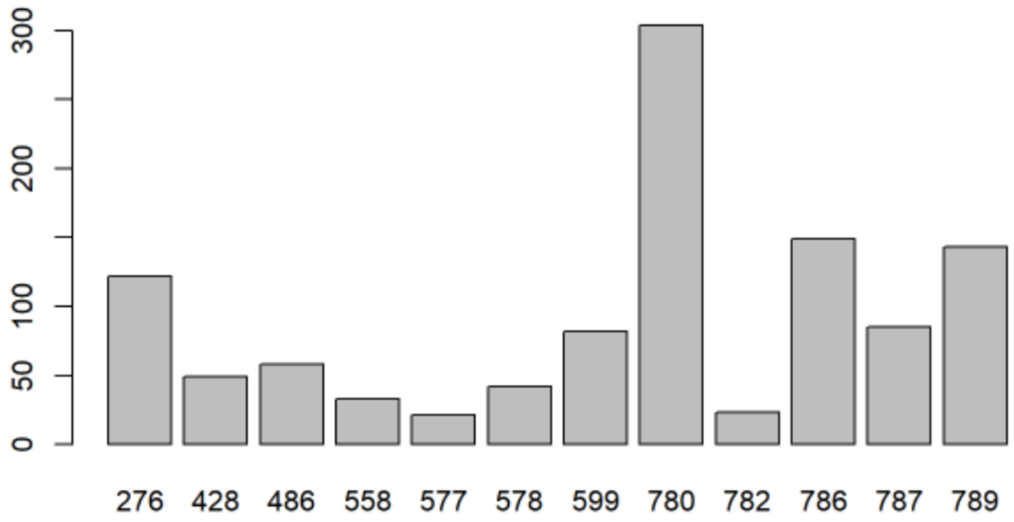

Figure 5. Barplot of Initial Diagnosis - related Group

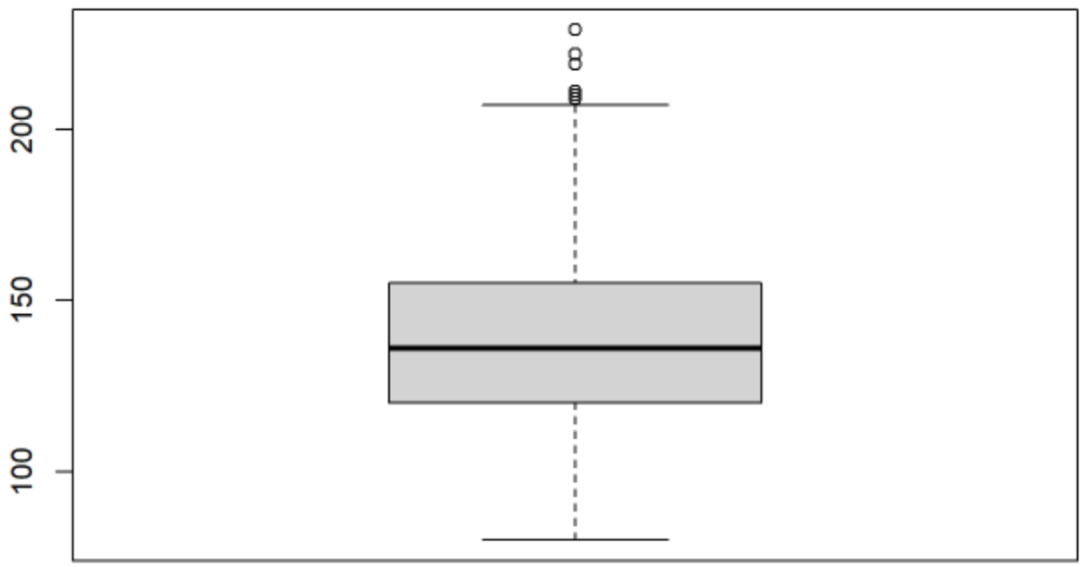

Figure 6. Boxplot of Systolic Blood Pressure

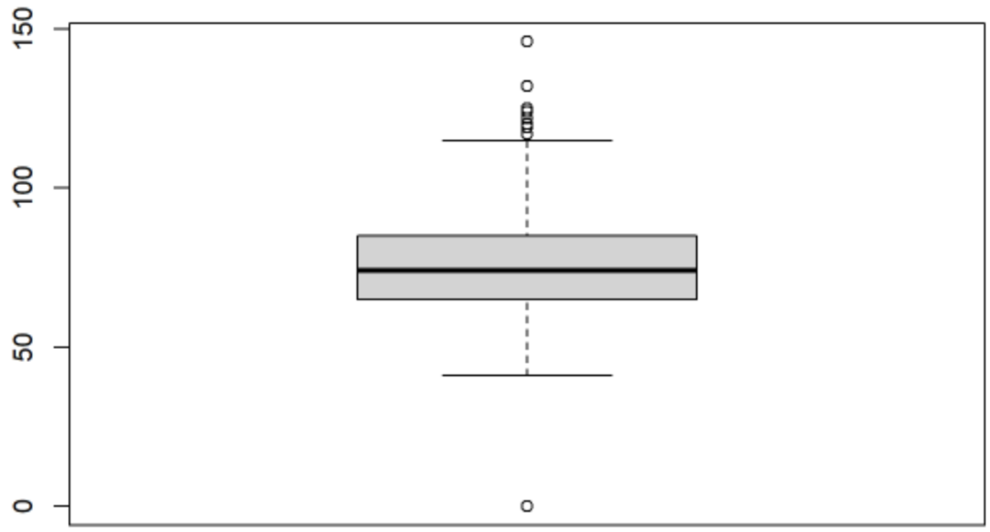

Figure 7. Boxplot of Diastolic Blood Pressure

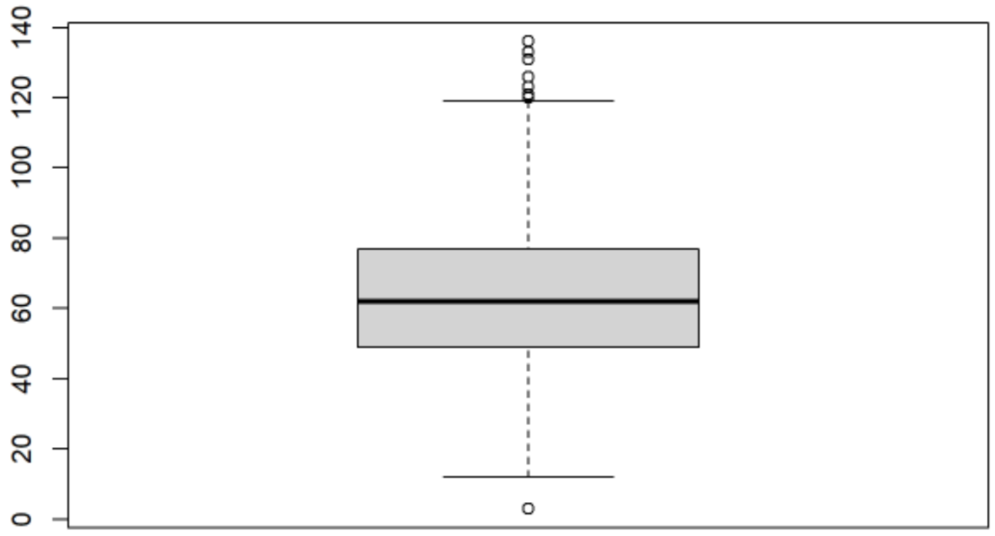

Figure 8. Boxplot of Pulse Pressure

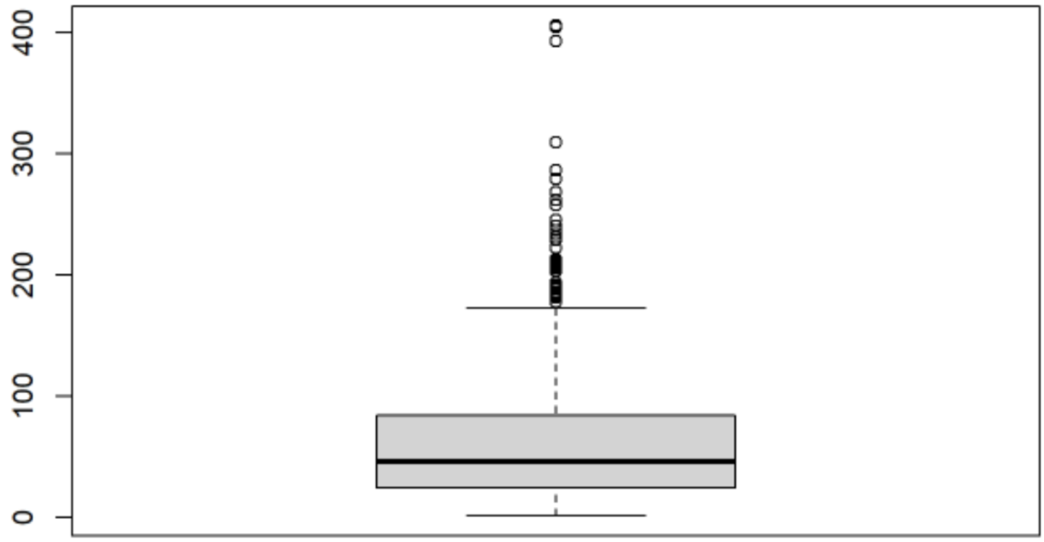

Figure 9. Boxplot of Length of Stay in the OU

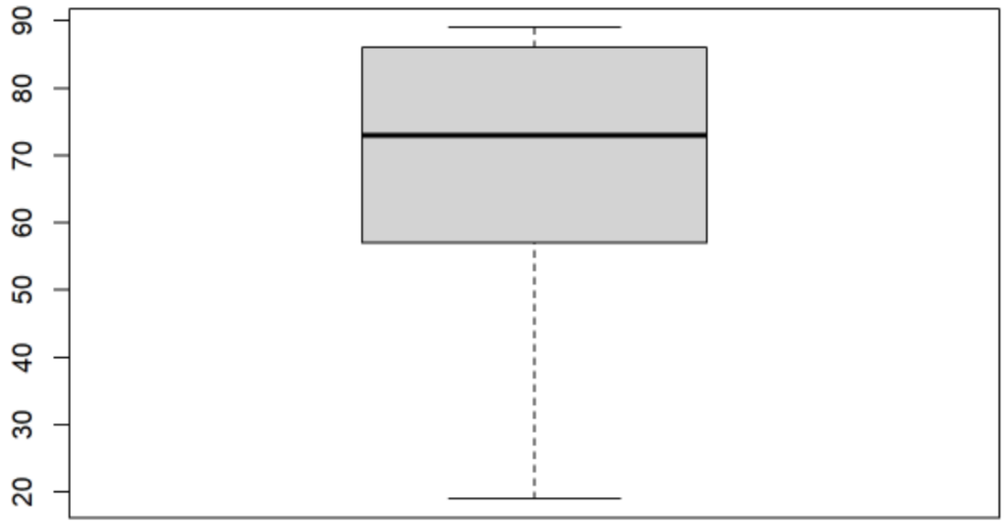

Figure 10. Boxplot of Age

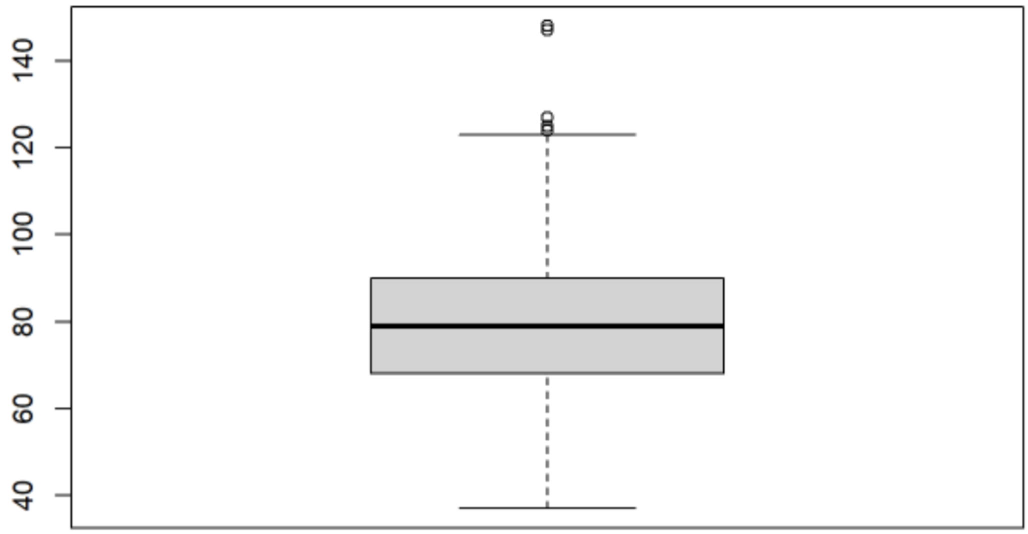

Figure 11. Boxplot of Pulse

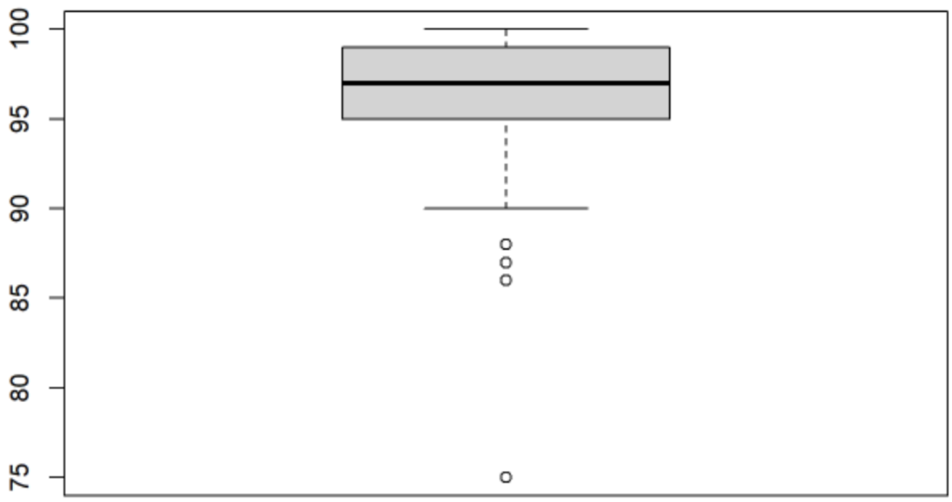

Figure 12. Boxplot of Pulse Oximetry

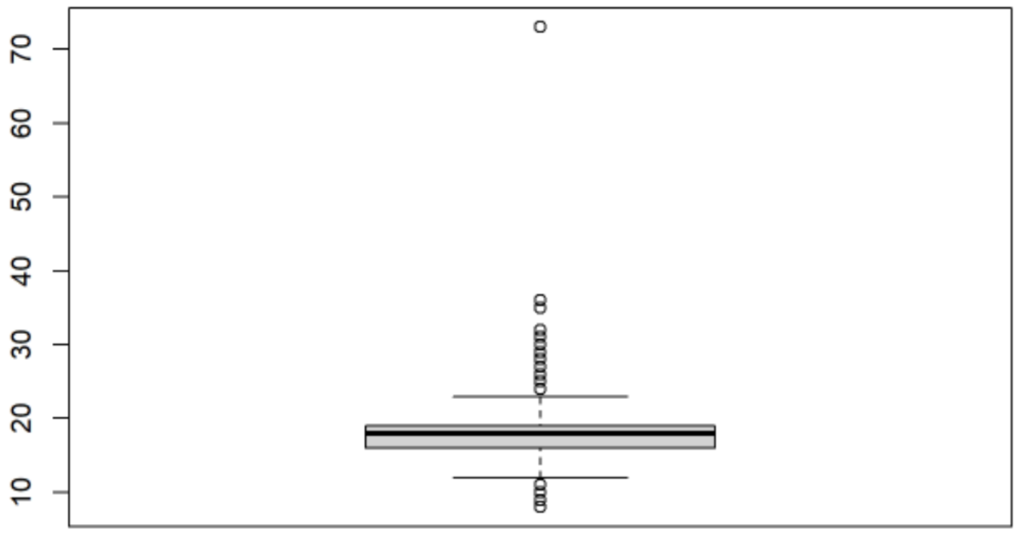

Figure 13. Boxplot of Respirations

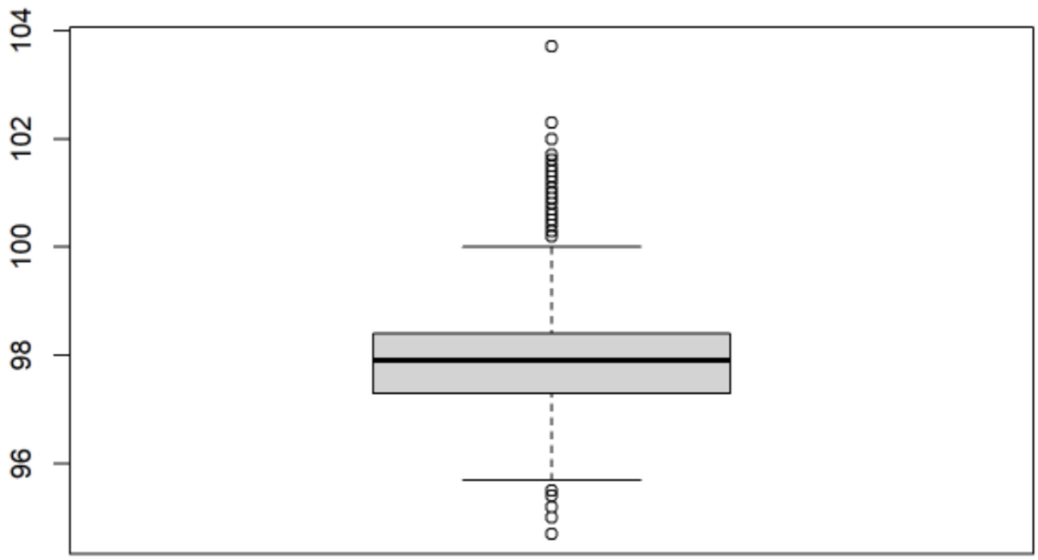

Figure 14. Boxplot of Temperature

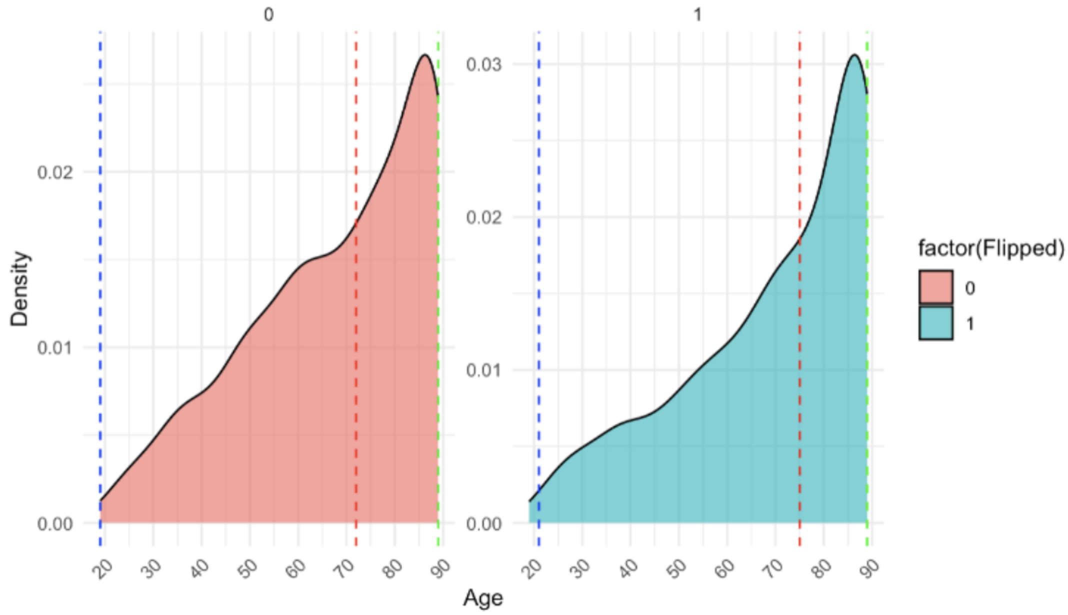

Figure 15. Distribution of Age - Flipped vs. NonFlipped Patients

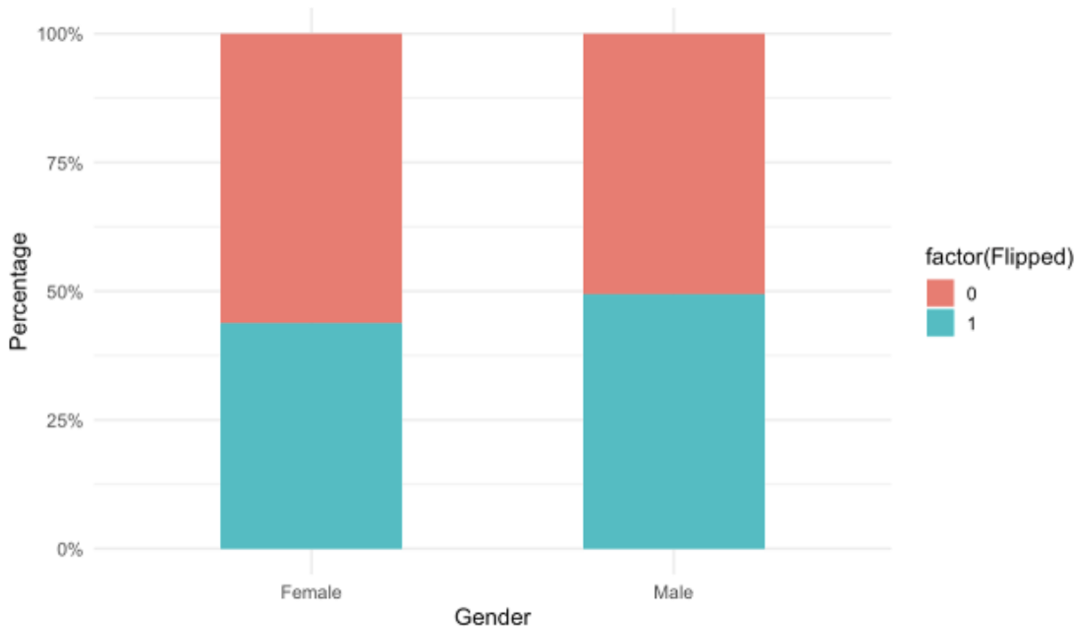

Figure 16. Distribution of Gender by Flipped Status

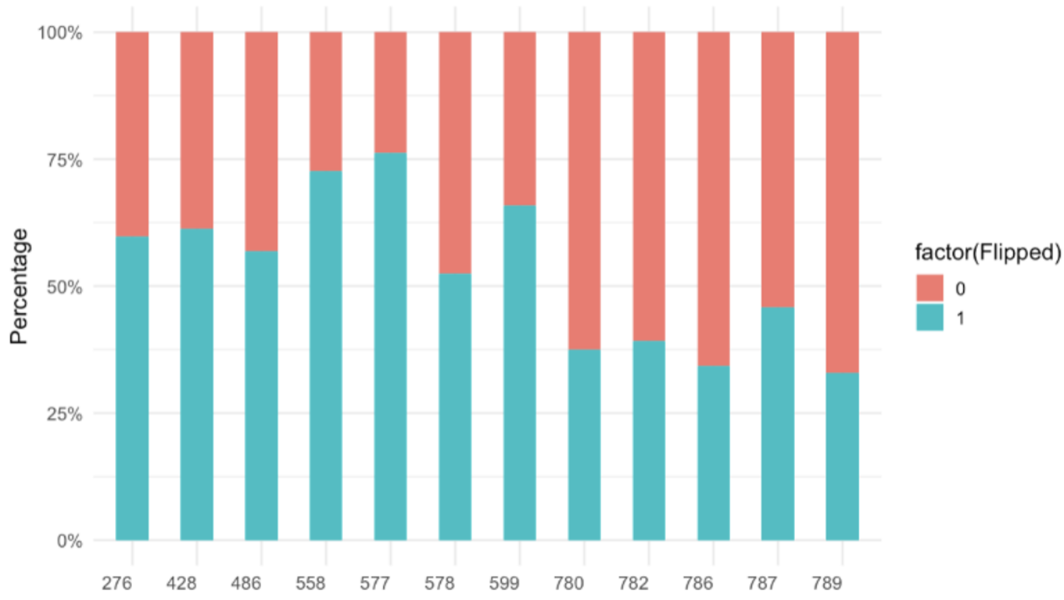

Figure 17. Distribution of DRG by Flipped Status

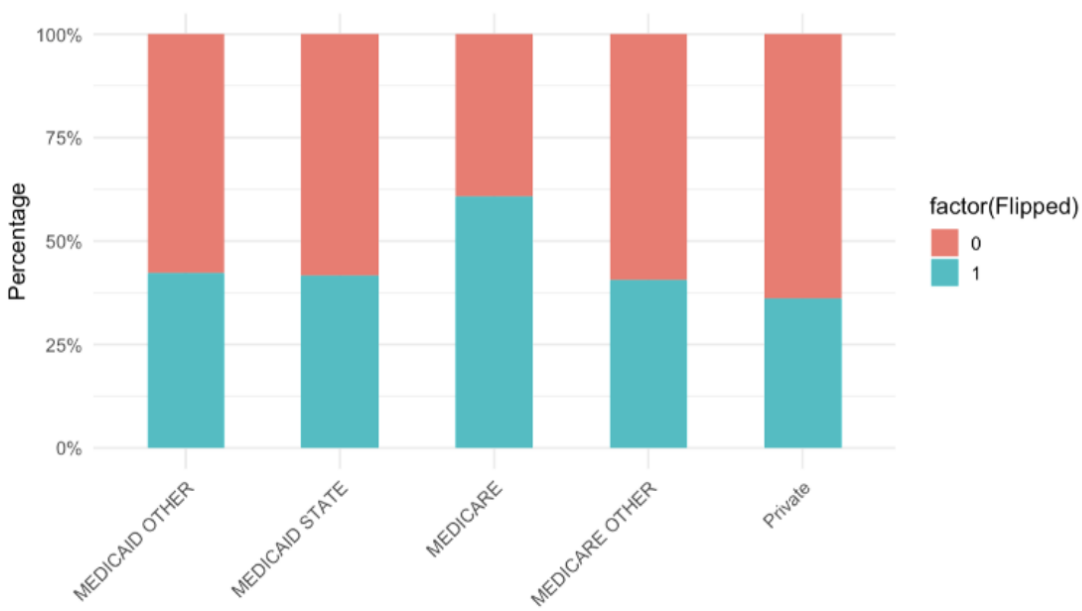

Figure 18. Distribution of Insurance Plans by Flipped Status

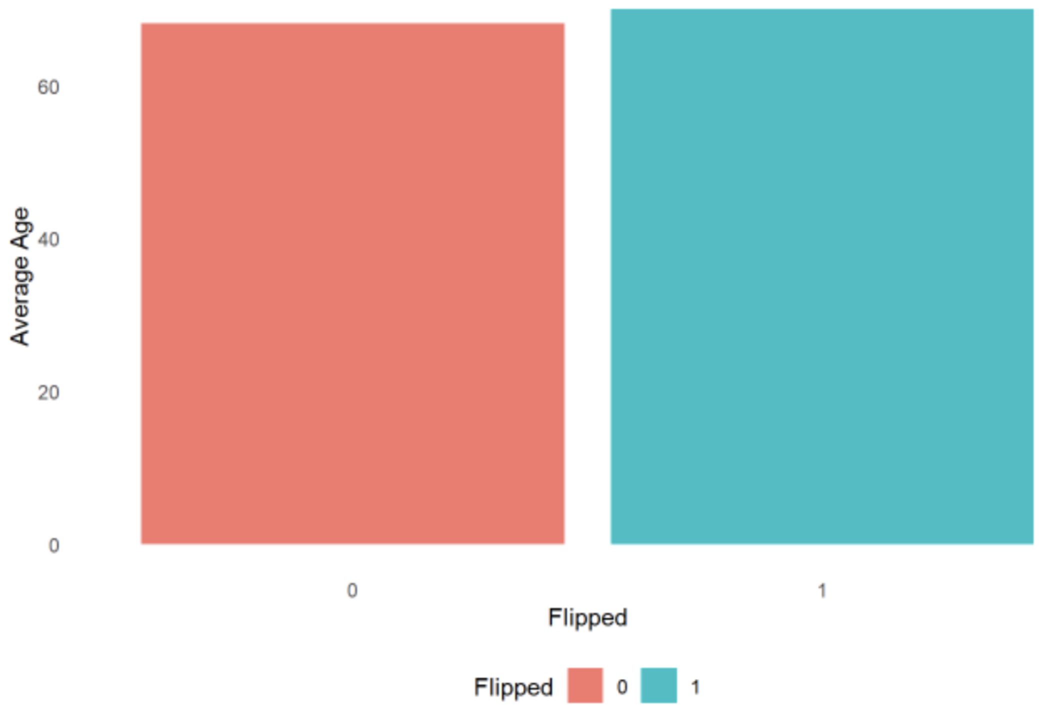

Figure 19. Average of Age by Flipped

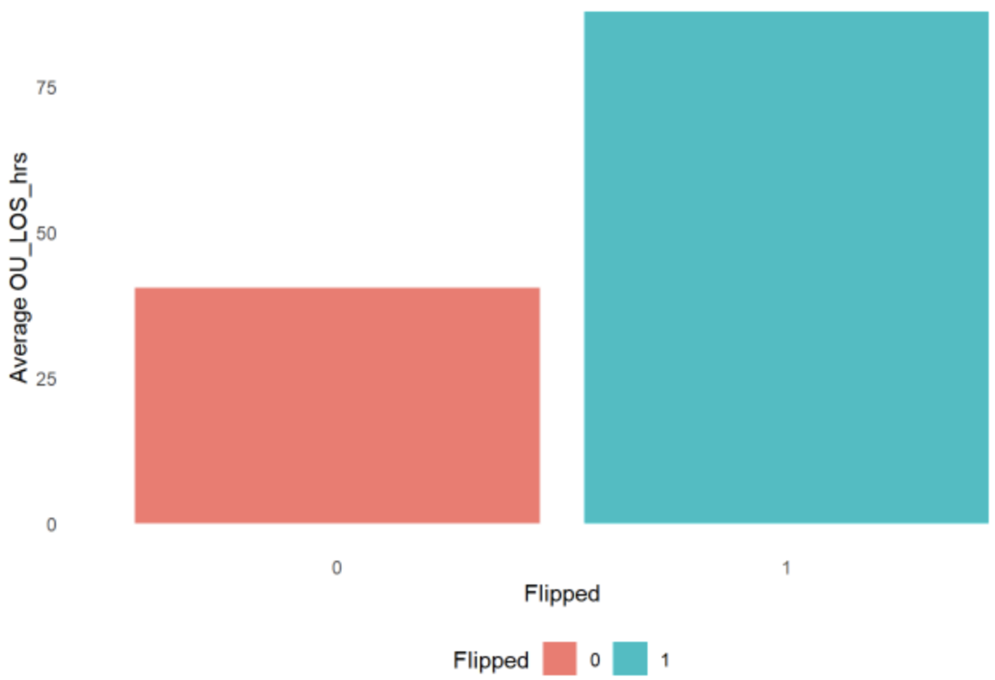

Figure 20. Average of OU_LOS by Flipped

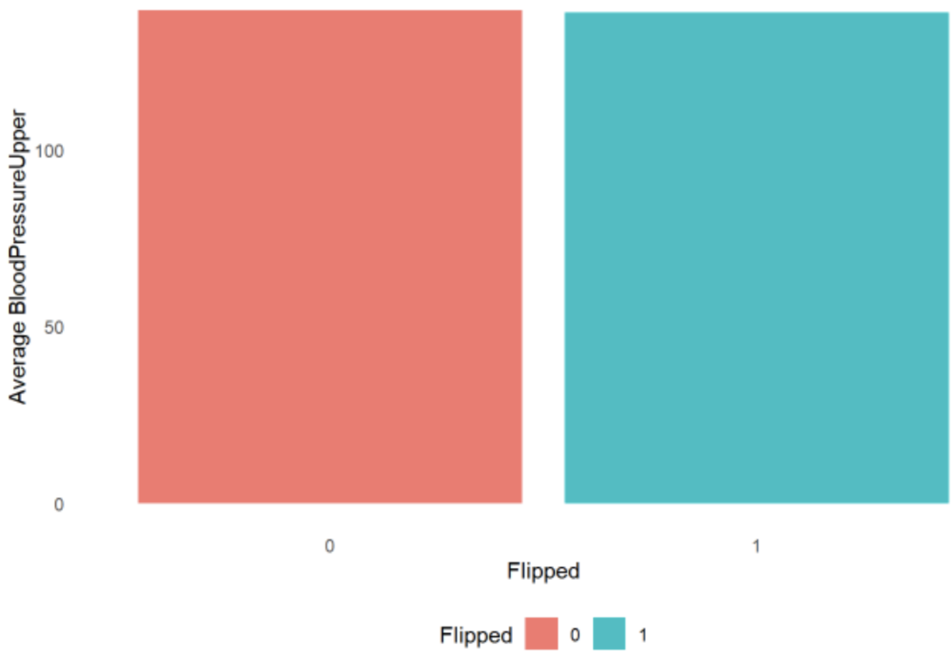

Figure 21. Average of BloodPressureUpper by Flipped

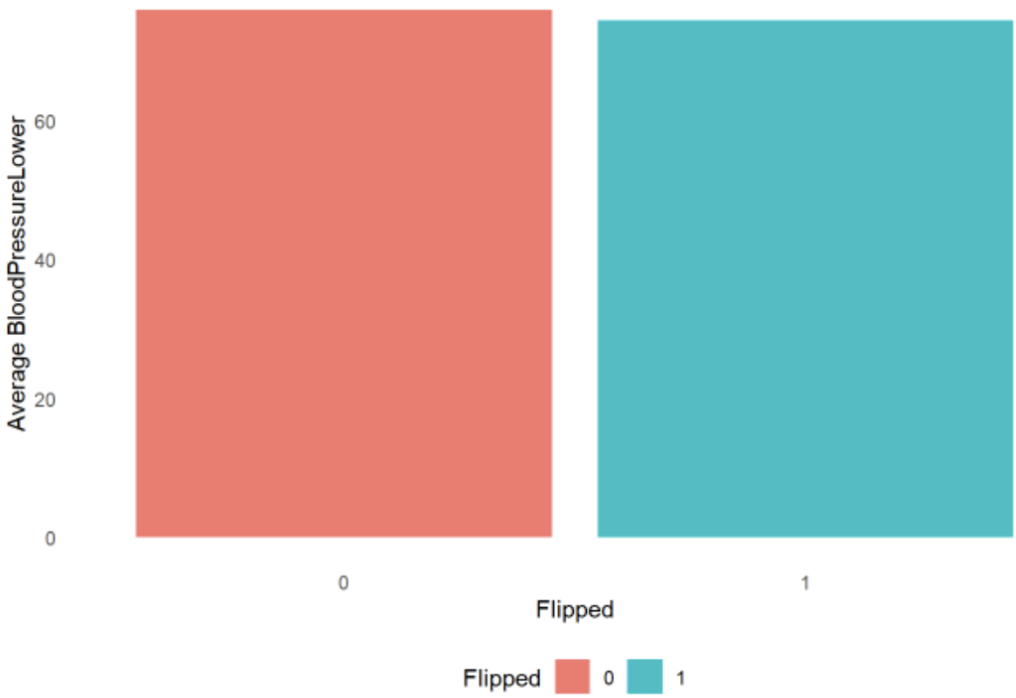

Figure 22. Average of BloodPressureLower by Flipped

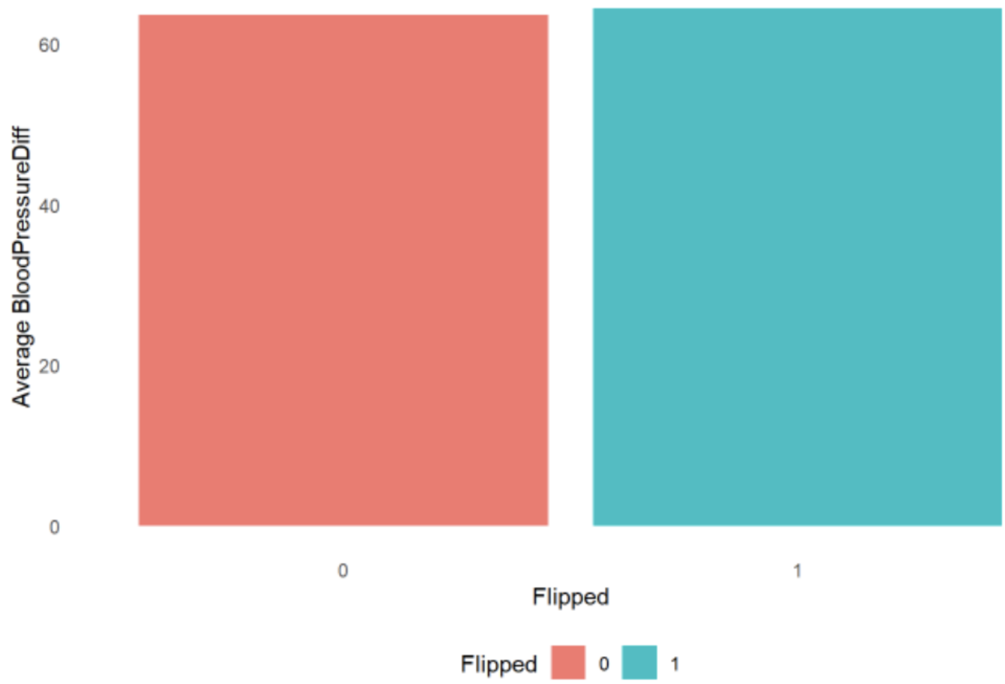

Figure 23. Average of BloodPressureDiff by Flipped

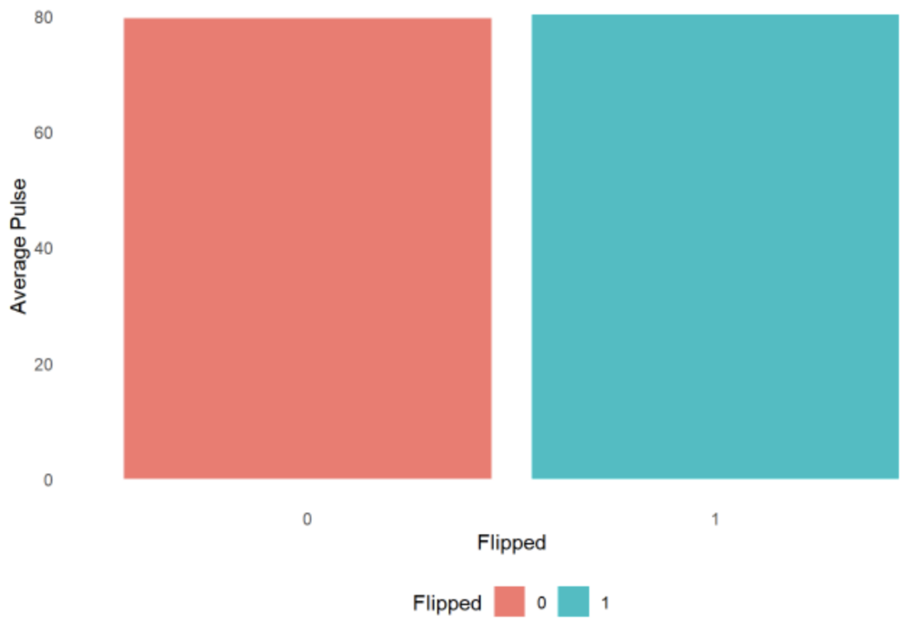

Figure 24. Average of Pulse by Flipped

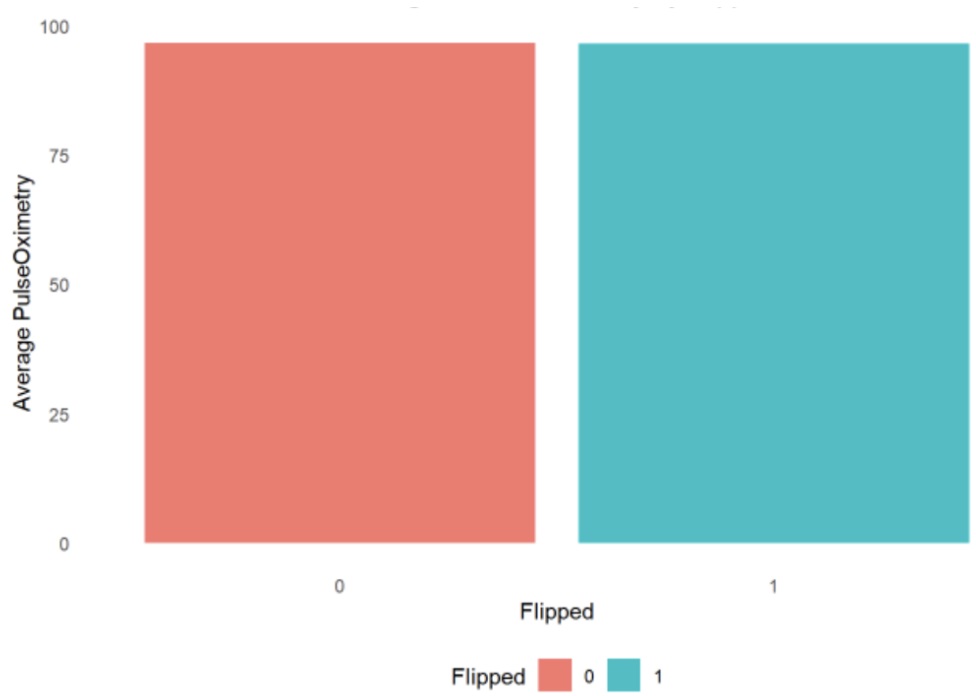

Figure 25. Average of PulseOximetry by Flipped

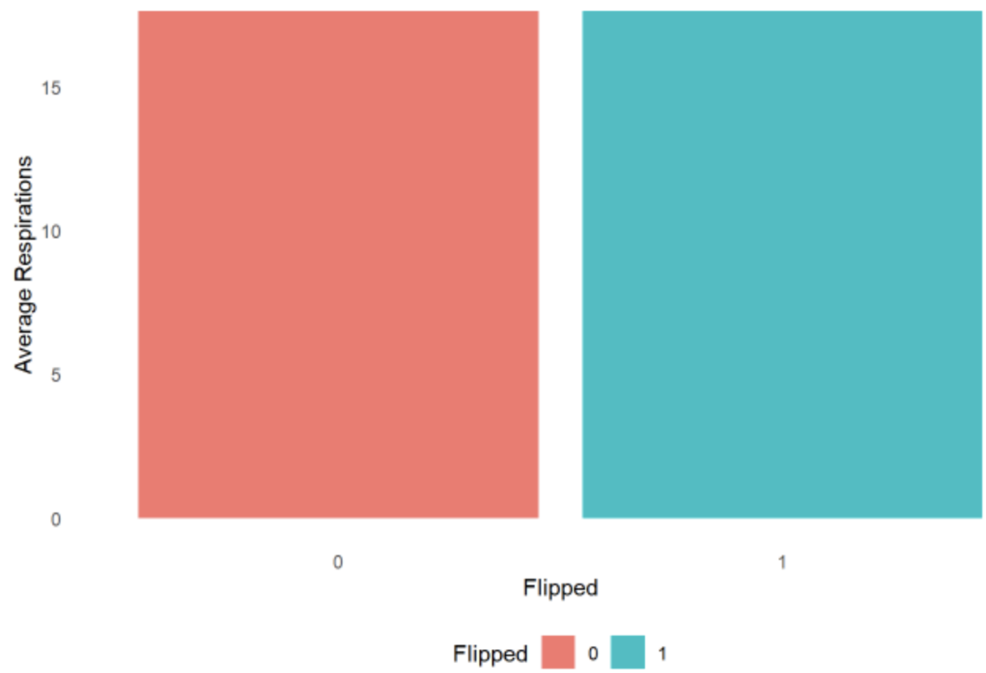

Figure 26. Average of Respirations by Flipped

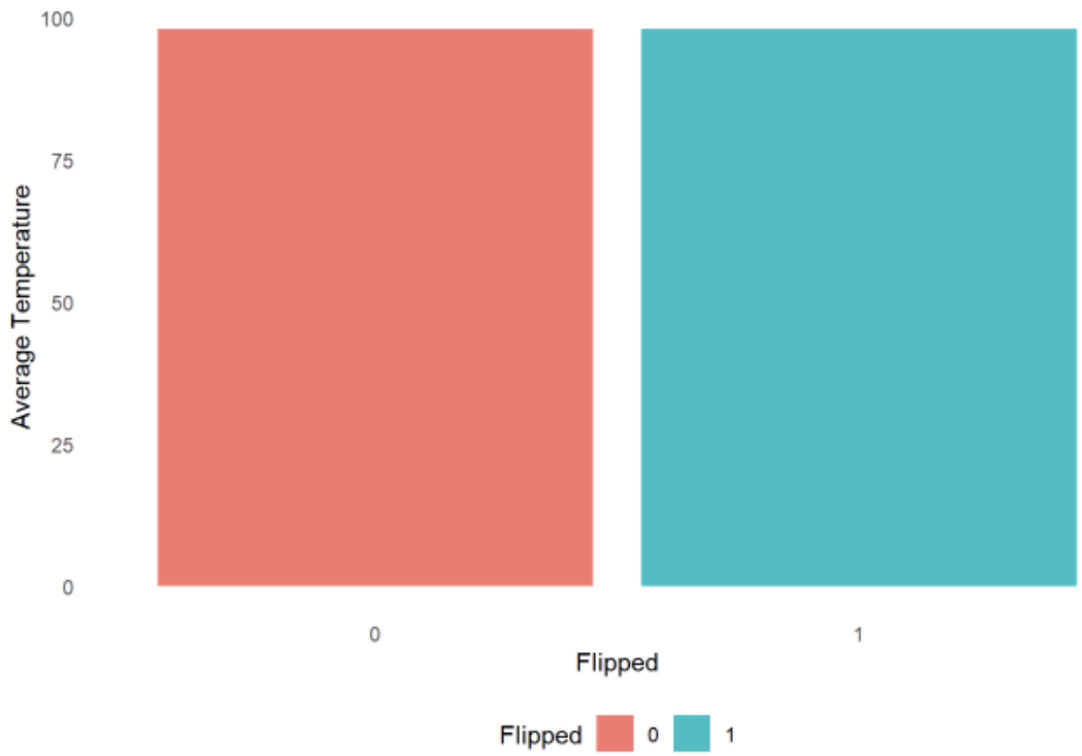

Figure 27. Average of Temperature by Flipped

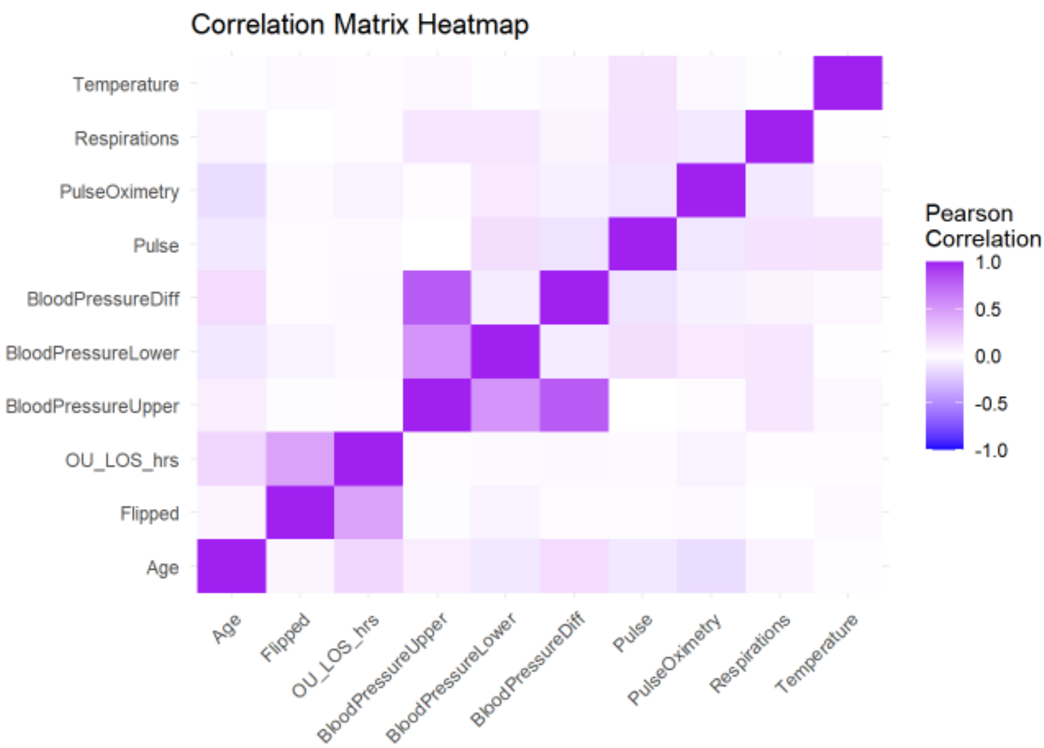

Figure 28. Correlation Matrix Heatmap for Numerical Variables

Categorical Variables	Correlation Coefficient
DRG01 vs. Flipped	**0.26**
Primary Insurance Category vs. Flipped	**0.19**
Gender vs. Flipped	**0.054**

Table 1. Correlation Table for Nominal Variables

```
glm(formula = Flipped ~ PrimaryInsuranceCategory + DRG01, family = "binomial",
    data = traindata)

Coefficients:
                                       Estimate Std. Error z value Pr(>|z|)
(Intercept)                             0.36026    0.35914   1.003 0.315799
PrimaryInsuranceCategoryMEDICAID STATE -0.22114    0.41235  -0.536 0.591760
PrimaryInsuranceCategoryMEDICARE        0.59823    0.32383   1.847 0.064695 .
PrimaryInsuranceCategoryMEDICARE OTHER -0.20723    0.31424  -0.659 0.509597
PrimaryInsuranceCategoryPrivate        -0.36403    0.34719  -1.049 0.294407
DRG01428                                0.20988    0.47110   0.446 0.655957
DRG01486                               -0.09782    0.43989  -0.222 0.824023
DRG01558                                0.59724    0.55710   1.072 0.283698
DRG01577                                0.90117    0.71319   1.264 0.206384
DRG01578                               -0.09153    0.49451  -0.185 0.853150
DRG01599                                0.28113    0.39046   0.720 0.471532
DRG01780                               -1.04758    0.29625  -3.536 0.000406 ***
DRG01782                               -0.44990    0.66640  -0.675 0.499599
DRG01786                               -1.05486    0.33497  -3.149 0.001637 **
DRG01787                               -0.56313    0.38183  -1.475 0.140257
DRG01789                               -0.91722    0.33998  -2.698 0.006980 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 919.51  on 665  degrees of freedom
Residual deviance: 847.17  on 650  degrees of freedom
AIC: 879.17

Number of Fisher Scoring iterations: 4
```

Figure 29. Logistic Regression

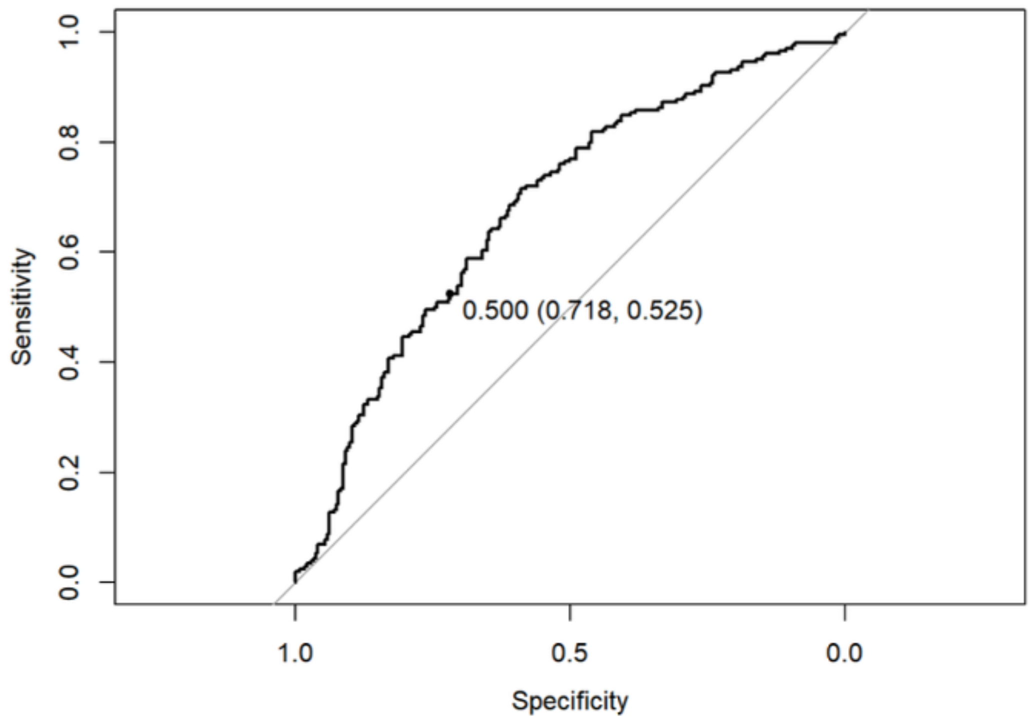

Figure 30. Gain Chart

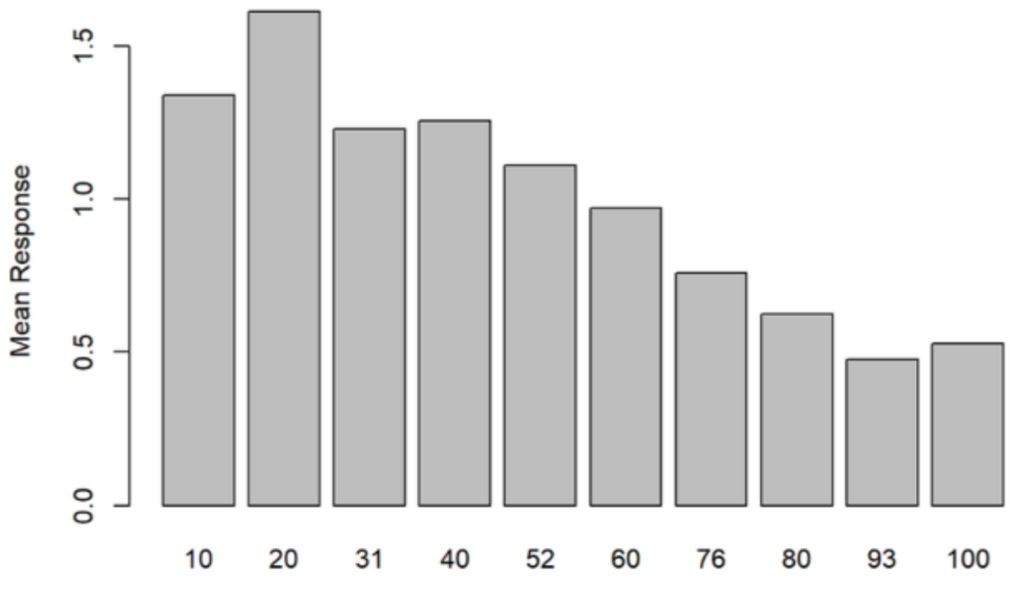

Figure 31. Decile-wise Lift Chart

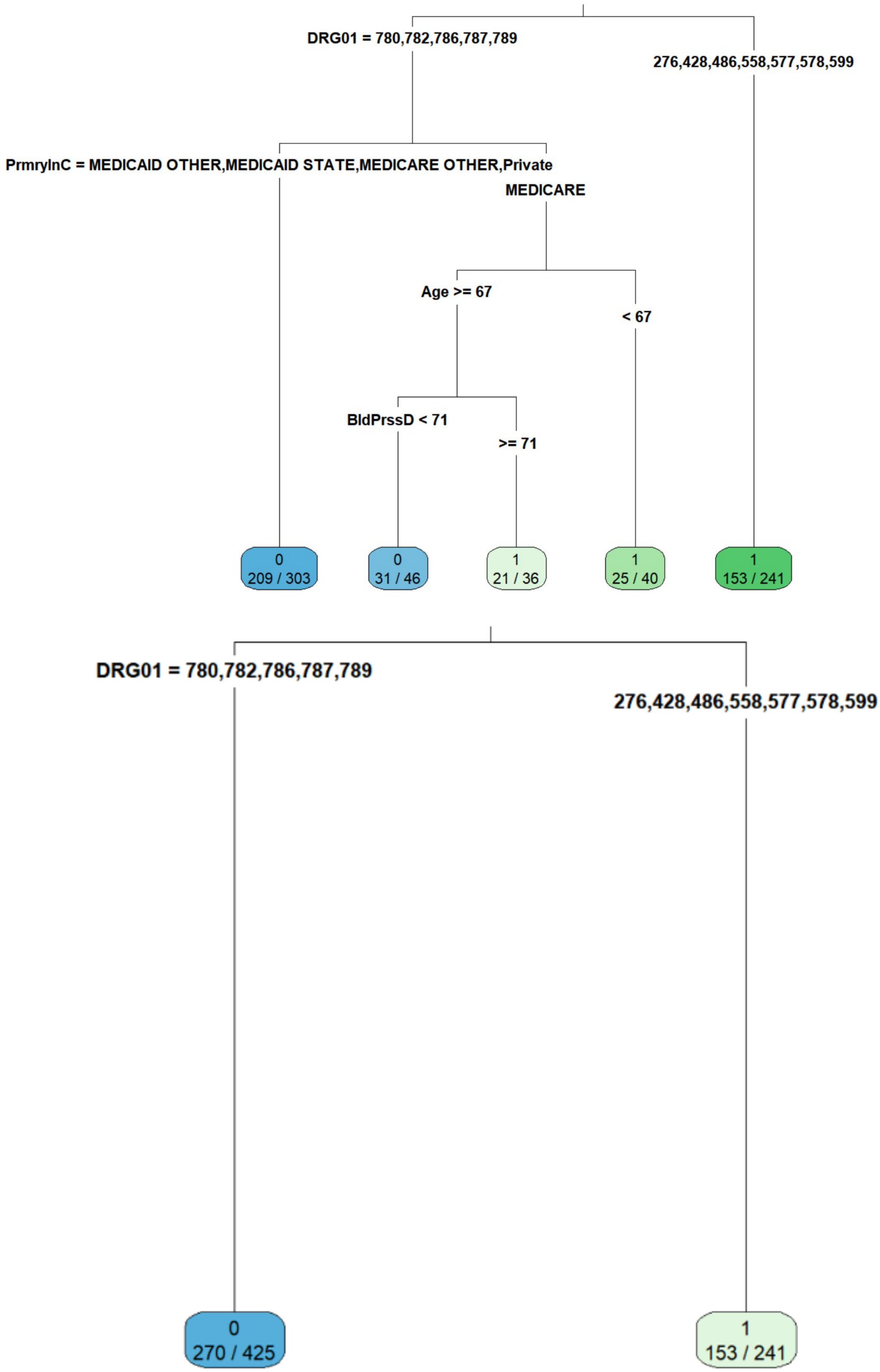

Figure 32. Classification Tree

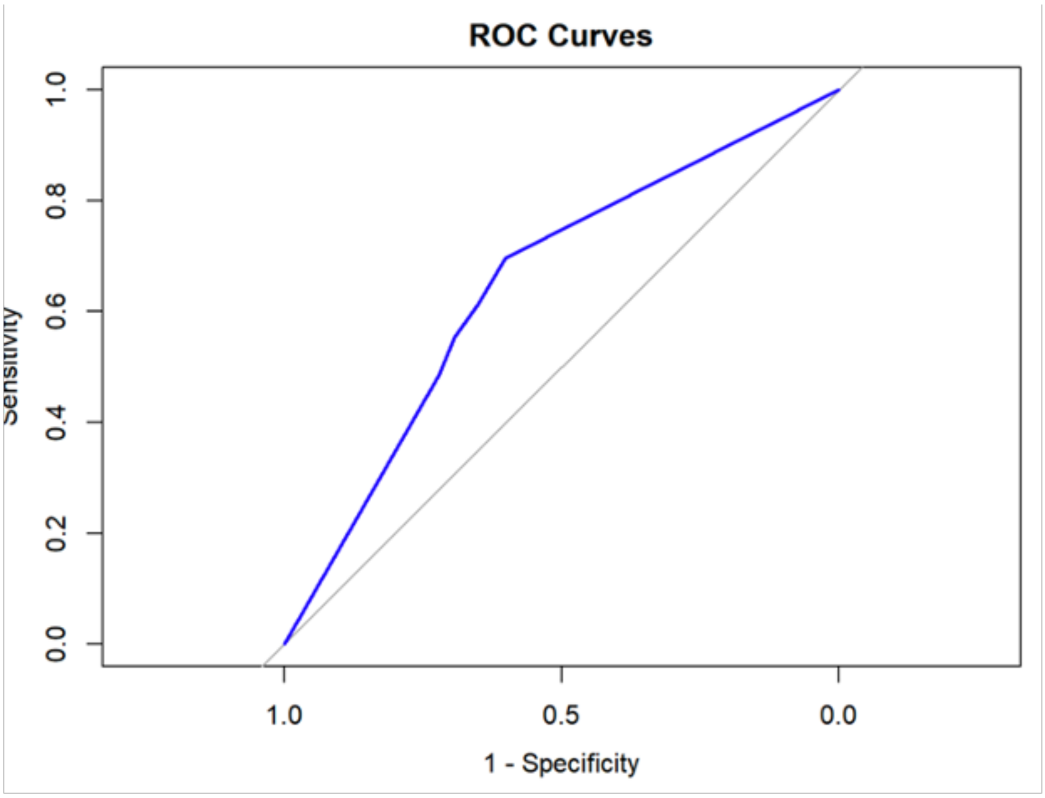

Figure 33. Classification Tree - ROC Curves

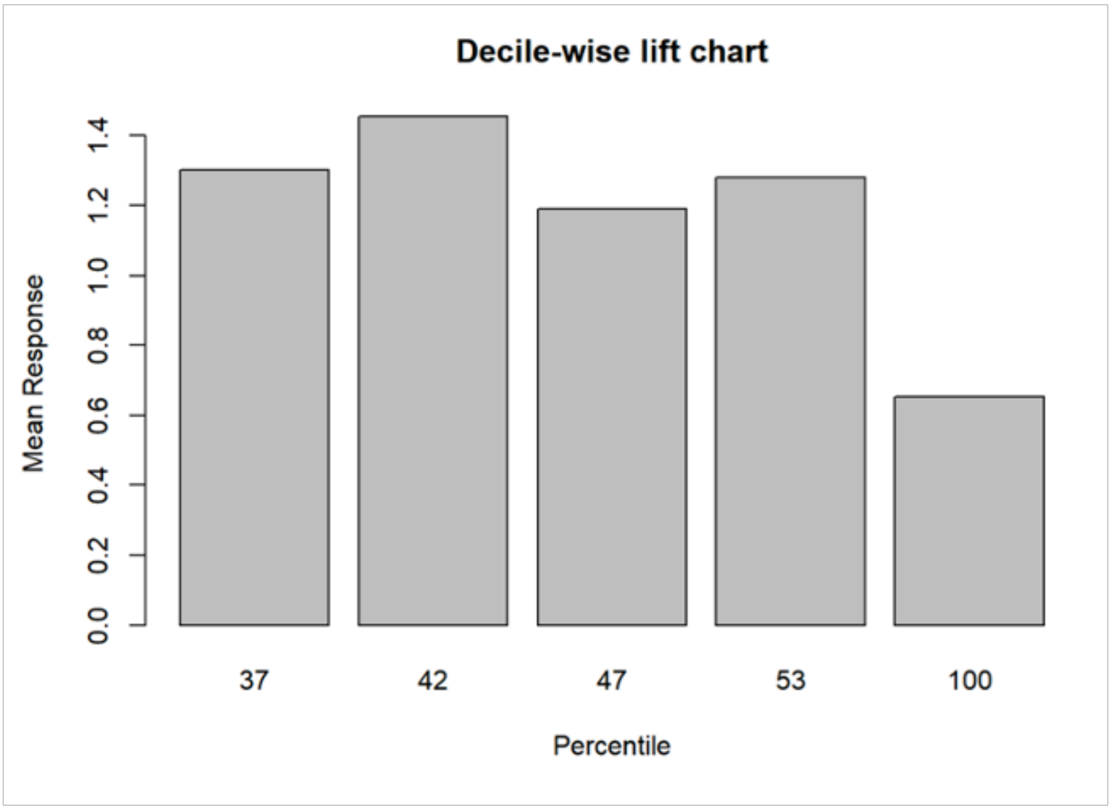

Figure 34. Classification Tree - Decile-wise Lift Chart

	Classification Tree	Random Forest	Logistic Regression
Accuracy	**0.6337**	**0.6337**	**0.6292**
Sensitivity	**0.6515**	**0.6805**	**0.7178**
Specificity	**0.6653**	**0.5784**	**0.5245**

Table 2. Predictive Performance Metrics

	Classification Tree	Random Forest	Logistic Regression
Flipped rate	**33.47%**	**34.4%**	**35.93%**
Inpatient mismatch rate	**34.85%**	**31.95%**	**28.22%**
Treated patients per week	**49**	**49**	**48**
Average LOS per patient(h)	**53.64**	**54.02**	**54.64**

Table 3. Model Application Performance in OU

Reimbursement Rates - Montanaro Hospital Receive/Day

	Observation Unit	Impatient Unit
Private	$600.00	$840.00
Medicare	$600.00	$840.00
Medicare Other	$600.00	$840.00
Medicaid	$450.00	$630.00
Medicaid Other	$450.00	$630.00
Average	$540.00	$756.00

Table 4. Price Assumption - Insurance Reimbursement Rates

Current OU Performance

Patient Metrics	Values
Total Number of Patients	9
Number of Flipped Patients	4
Number of Non-Flipped Patients	5
% Flipped patient	45.00%
Revenue OU / day	$2,700.00

Performance - Recommended Model

Patient Metrics	Values
Total Number of Patients	10
Number of Flipped Patients	3
Number of Non-Flipped Patients	7
% Flipped patient	33.47%
Revenue OU / day	$3,780.00

Performance - Optimization Model

Patient Metrics	Values
Total Number of Patients	11
Number of Flipped Patients	4
Number of Non-Flipped Patients	7
% Flipped patient	36.36%
Revenue OU / day	$3,780.00

Table 5. Revenue Comparison between Models

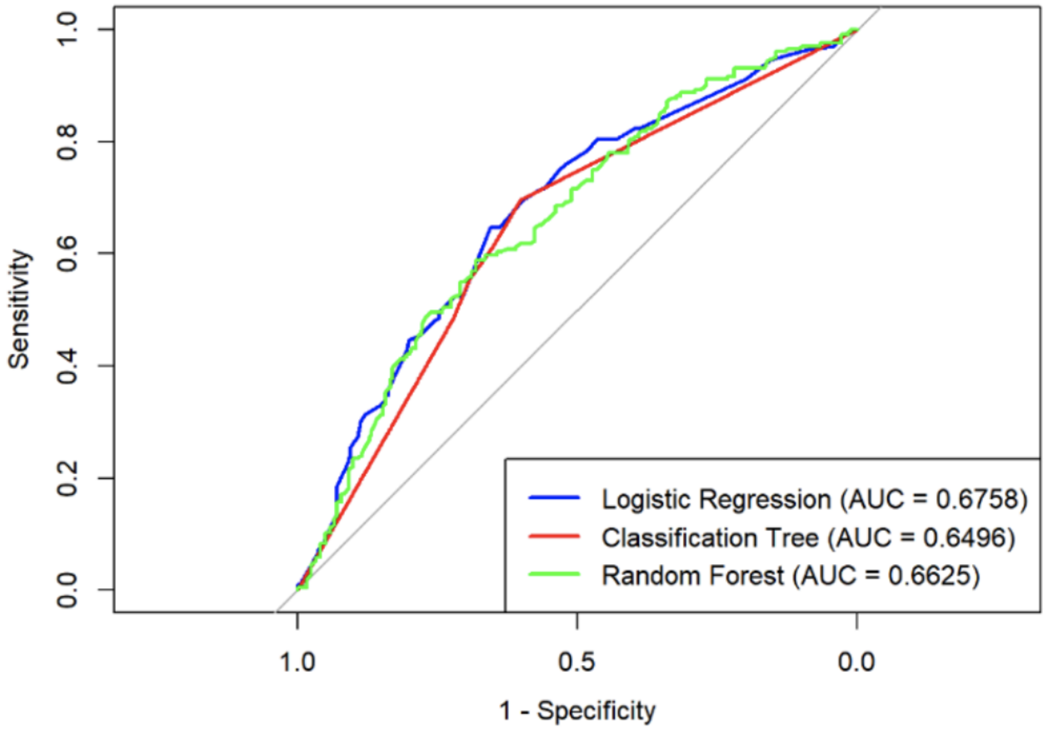

Figure 35. ROC Curves - Logistic Regression, Classification Tree, and Random Forest

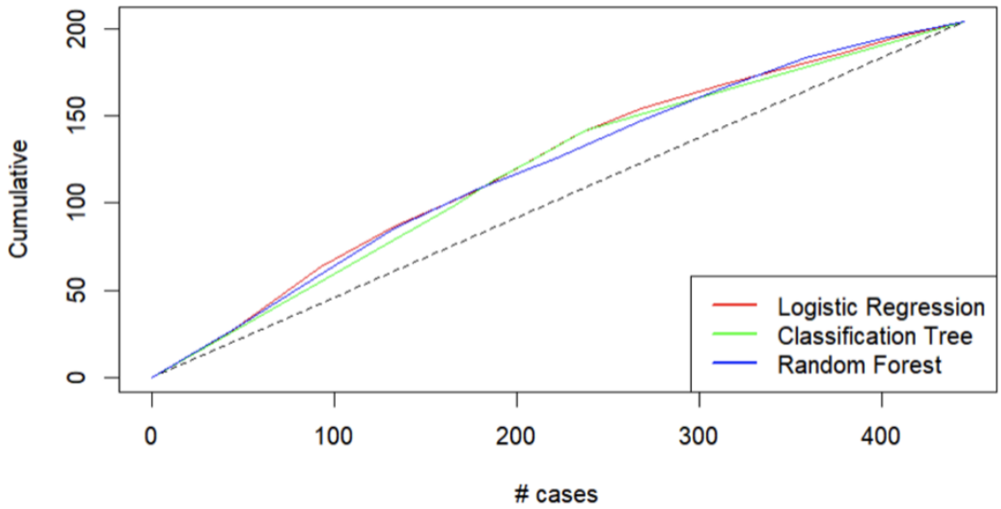

Figure 36. Lift Chart - Logistic Regression, Classification Tree, and Random Forest

Revenue per non-flipped patient/day	$540.00
Revenue per flipped patient/day	$756.00

Decision Variables

Number of Flipped Patients	4
Number of Non-Flipped Patients	7
Percentage of flipped patient	36.36%

Constraints

	LHS	Sign	RHS
Percentage of Flipped bw 0% and 100%	0	<=	36.36%
	36.36%	<=	100%
Percentage of flipped patients should be at least 20%	20%	<=	36.36%
	45%	>=	36.36%
Number of flipped patients	4	<=	4
	4	>=	3
Number of non flipped patients	7	<=	7
	7	>=	5

Objective

Revenue	$6,804.00

Figure 37. Optimization Model