Temporal Patterns in Surgical Patient Outcomes

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Introduction

Context and Background

Since the rise of the coronavirus disease (COVID-19), there has been a surge in the concern of a complication in healthcare industries worldwide. The shortage of healthcare professionals has been an increasingly discussed topic among citizens and healthcare providers alike as millions of people experienced the threat of a global pandemic. In general, the scarcity of medical industry professionals has led to a decline in the quality and availability of care in hospitals. (Džakula and Danko, 2022) It is widely known and studied that insufficient amounts of sleep and extended work shifts risk negative impacts on one's cognitive and motor performance. (Alhola and Päivi, 2007)Due to the risk of underperformance of healthcare workers, particularly surgeons, there has been a push to limit resident work hours to mitigate potential errors that may impact patients.

Given that the healthcare sector is one of high stakes that often demands medical professionals to work extensive shifts due to short staff and increased patient attendance, the risk of long work hours cannot be ignored. Furthermore, just as extended hours of work may lead to fatigue and a compromise in cognitive and physical tasks, typical workweek progression may lead to similar results. (Sessler et al., 2011) This study aims to address the association between multiple time-related factors and the resulting outcome of patients' operation cases.

These are the four main objectives of this case study (Sessler et al., 2011):

1) Is there any association between whether or not a patient's operation results in 30-day mortality and the time of the day in which the operation occurs? How about the day of the week?

2) Is there any association between whether or not a patient experiences in-hospital complications and the time of day in which the operation occurs? How about the day of the day of the week?

Answering these objectives will help healthcare industry leaders better understand the possible critical risks of progression in time from morning to evening as well as progression in days of the week from Monday to Friday of surgeons on patient operation outcomes, particularly mortality and complication risks.

The Data

The data for this study was collected and provided by the Cleveland Clinic Lerner Research Institute. The data is formatted as patient-level observations that comprise of 32,001 surgical patients from the Cleveland Clinic between January 2005 and September 2010. The data collection window consisted of the hours of 6 am to 7 pm during the work weekdays. It is important to note that the surgical procedures were limited to elective operations since urgent or semi-urgent procedures, which are riskier, are often performed later in the workday even without being offically labeled as emergencies. The variables included in the dataset are the patient's age, gender, race, ASA physical status, body mass index, United States Agency for Healthcare Research and Quality's Clinical Classifications Software (AHRQ-CCS) Procedure Category, Charlson Comorbidity Index, 30-Day Mortality Risk Stratification Index, In-Hospital Complications Risk Stratification Index, overall incidence of 30-day Mortality for each AHRQ-CCS procedure category, overall Incidence of In-hospital Complications for each AHRQ-CCS procedure category, operation hour, day of the week, month of the year, phase of the moon, whether or not the patient resulted in having 30-day mortality, whether or not the patient resulted in having in-hospital complications, and whether or not the patient has the following diseases/disorders: cancer, cardiovascular/cerebrovascular disease, dementia, diabetes, digestive disease, osteoarthritis, psychiatric disorder, pulmonary disease. (some variable definitions provided in Appendix)

Exploratory Data Analysis

The initial stages of exploratory data analysis consisted of viewing the distribution of each of the patient descriptor potential predictors. Viewing the distribution of variables age, gender, race, ASA Physical status, and body mass index (Appendix: Images 1-5) assisted in identifying the best measure of center and spread for summary statistics.

Summary Statistics of Baseline Risk Factors for Patients

Predictors	Summary.Statistics
Age(mean/SD)	
Age	57.66 ± 15.04
Gender (count/%)	
Male	14768 (46.15 %)
Female	17230 (53.84 %)
Race (count/%)	
Caucasian	26488 (82.77 %)
African American	3790 (11.84 %)
Other	1243 (3.88 %)
ASA Physical Status (count/%)	
I-II	17261 (53.94 %)
III	13677 (42.74 %)
IV-VI	1055 (3.3 %)
BMI (median/IQR)	
Body Mass Index	28.19 [24.6 , 32.81]
Diseases/Disorders (count/%)	
Cancer	10958 (34.24 %)
Cardiovascular/cerebrovascular disease	16176 (50.55 %)
Dementia	242 (0.76 %)
Diabetes	4166 (13.02 %)
Digestive disease	7037 (21.99 %)
Osteoarthritis	5719 (17.87 %)
Psychiatric disorder	2910 (9.09 %)
Pulmonary disease	3493 (10.92 %)
Indexes (median/IQR)	
Charlson Comorbidity Index	0 [0 , 2]
Risk Stratification Index (30-day mortality)	-0.3 [-1.24 , 0]
Risk Stratification Index (in-hospital complications)	-0.27 [-0.84 , 0]

Based on the visualizations and the summary statistics above it notable that the age of the patients is normally distributed centered around 57.66 years old, there are more female patients, and the racial demographic of the patients is largely Caucasian. The patients tend to be centered more around the lower to middle class of ASA physical status meaning they are mostly in relatively good health. The BMI of the patients are normally distributed but slightly skewed towards higher BMI with a center at 28.19 which is relatively overweight. It is also worth noting that roughly half the patient population has a cardiovascular or cerebrovascular disease, about a third of the patients have cancer, and about a fifth of the patients have a digestive disease. The median Charlson Comorbidity Index of the patient population is roughly 0. This means no comorbidities were found and therefore generally there weren't more than one disease simultaneously found in one patient. These summary statistics show that certain demographics of the patients are quite atypical in comparison to the general population.

Summary Statistics of Case Frequencies (Count/%)

Predictors	Summary.Statistics
Hour of Operation	
6:00	562 (1.76 %)
7:00	10631 (33.22 %)
8:00	3807 (11.9 %)
9:00	1664 (5.2 %)
10:00	2501 (7.82 %)
11:00	2855 (8.92 %)
12:00	2763 (8.63 %)
13:00	2623 (8.2 %)
14:00	2063 (6.45 %)
15:00	1267 (3.96 %)
16:00	745 (2.33 %)
17:00	356 (1.11 %)
18:00	163 (0.51 %)
19:00	1 (0 %)
Day of the Week	
Monday	7005 (21.89 %)
Tuesday	7008 (21.9 %)
Wednesday	6266 (19.58 %)
Thursday	5635 (17.61 %)
Friday	6087 (19.02 %)
Month	
January	2670 (8.34 %)
February	2506 (7.83 %)
March	2697 (8.43 %)
April	2698 (8.43 %)
May	2654 (8.29 %)
June	2994 (9.36 %)
July	2325 (7.27 %)
August	3177 (9.93 %)
September	3208 (10.02 %)
October	2689 (8.4 %)
November	2544 (7.95 %)
December	1839 (5.75 %)
Phase of Moon	
New Moon	7708 (24.09 %)
First Quarter	8100 (25.31 %)
Full Moon	8051 (25.16 %)
Last Quarter	8142 (25.44 %)

The table above as well as the Images 9-12 (Appendix) display the distribution of the patient's operations by measures of time. When viewing the distribution of operation cases of the time of day it is worth noting that a third of operation cases took place from the span of 7-8am and a steady flow of operation cases take place from 10am to 2pm. When viewing the distribution of operation cases over the days of the week, there are only slightly more cases in the beginning of the week. The distribution of cases over the span of months has some differences with the highest concentrations being in August and September. Lastly the distribution of operations over moon phases are quite uniform.

The last significant portion of EDA was visualizing the possible relationship between the time-related predictors and the response variables of whether or not a patient had in-hospital complications and 30-day mortality. Image 15A) is a box plot displaying the relationship between hour of operation and the binary variable of 30-day mortality. It shows that operations of patients that have 30-day mortality tend to happen slightly later in the day than operations of patients that do not have 30-day mortality. Image 15B) is a box plot that displays the relationship between the hour of operation and the binary variable of in-hospital complication. It shows that operations of patients that have in-hospital complications tend to be relatively in the same range of time as operations of patients that do not have in-hospital complications. Image 16A) is a series of bar plots that show the count of the binary variable 30-day mortality over the days of the week. It shows there is a noticeably decreasing number of patients without 30-day mortality as the week goes on. Image 16B) is a series of bar plots that show the count of the binary variable in-hospital complication over the days of the week. It shows there is also a decreasing number of patients without in-hospital complication as the week goes on. (Appendix)

Methodology

Model Choice: Logistic Regression Model

To model the relationship between the measures of time (hour of the operation, day of the week) in which the surgical operations took place and the response variables of 30-day mortality and in-hospital complication, I decided to create two logistic regression models. The reason behind this choice is due to the response variables being two separate binary outcomes. I decided to utilize the variables that the research objective highlight such as hour of operation and day of the week, but I also accounted for other variables. In both models I added the patients' age, Body Mass Index, ASA Physical Status, and Charlson Comorbidity Index because these are all possible predictors that are associated with the general wellness and health complications of a person which would likely explain some variability in the response variables of 30-day mortality and in-hospital complication. In the logistic regression model with 30-day mortality as the response variable I accounted for the Risk Stratification Index (30-day mortality) to account for procedures and diagnoses the patient undergoes. More specifically, the RSI allows the 30-day mortality outcome to be compared equally across institutions. This was also done in the logistic regression model with in-hospital complication as the response variable but instead I accounted for the Risk Stratification Index (in-hospital complications). Additionally in both models I accounted for the overall incidence of the response variables for each AHRQ-CCS Procedure Category. This adjustment was implemented to guarantee thorough control for potential confounding factors linked to variations in the exposures of interest concerning the different procedure types of each patient. (Sessler, Daniel I., et al, 2011)

Model 1: 30-Day Mortality

$$\begin{aligned}log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \beta_1 \times RSIMortality_i + \beta_2 \times OverallIncidenceMortality_i + \beta_3 \times hour_i \\ + \beta_4 \times (day_i = Monday) + \beta_5 \times (day_i = Thursday) + \beta_6 \times (day_i = Tuesday) + \beta_7 \times (day_i = Wednesday) \\ + \beta_8 \times Age_i + \beta_9 \times BMI_i + \beta_{10} \times (ASAstatus_i = I - II) + \beta_{11} \times (ASAstatus_i = III) \\ + \beta_{12} \times (ASAstatus_i = IV - VI) + \beta_{13} \times CCI_i + \epsilon_i\end{aligned}$$

$\pi =$ probability of a patient having 30-day mortality

$where\ Y_i|X_i\beta \sim Bernoulli(\pi_i)$

$\epsilon_i \sim N(0, \sigma)$

Model 2: In-Hospital Complication

$$\begin{aligned}log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \beta_1 \times RSIComplication_i + \beta_2 \times OverallIncidenceComplication_i + \beta_3 \times hour_i \\ + \beta_4 \times (day_i = Monday) + \beta_5 \times (day_i = Thursday) + \beta_6 \times (day_i = Tuesday) + \beta_7 \times (day_i = Wednesday) \\ + \beta_8 \times Age_i + \beta_9 \times BMI_i + \beta_{10} \times (ASAstatus_i = I - II) + \beta_{11} \times (ASAstatus_i = III) \\ + \beta_{12} \times (ASAstatus_i = IV - VI) + \beta_{13} \times CCI_i + \epsilon_i\end{aligned}$$

$\pi =$ probability of a patient having In-Hospital Complication

$where\ Y_i|X_i\beta \sim Bernoulli(\pi_i)$

$\epsilon_i \sim N(0, \sigma)$

The coefficients are β_0 for the intercept, β_1 for the Risk Stratification Index (30-Day Mortality)/(In-Hospital Complication), β_2 for the Overall Incidence of 30-Day Mortality/In-Hospital Complication for Each AHRQ-CCS Procedure Category, β_3 for operation hour, β_4-β_7 for the days of the week with the baseline being Friday, β_8 for patients' age, β_9 for patients' body mass index, β_{10}-β_{12} for ASA Physical Status,β_{13} for Charlson Comorbidity Index, and ϵ_i for the residual error for the i^{th} patient.

Model Assumptions and Diagnostics

The model assumptions needed to fit these models were linearity of the log-odds, independence of the observations, absence of perfect multicollinearity, and the data being obtained from a random process. Image 17) shows there is linearity between the predictor hour of operation and the log odds of 30-day mortality. Image 18) shows there is linearity between the hour of operation and the log-odds of in-hospital complications. Image 19) shows there is not -1/+1 correlation between the numerical predictors therefore no perfect multicollinearity is present.

Results

Table 1: 30-Day Mortality Model Coefficients/Summary Stats

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-17.708	544.451	-0.033	0.974
Risk Stratification Index (30-Day Mortality)	1.101	0.083	13.293	0.000
Overall Incidence of 30-Day Mortality for Each AHRQ-CCS Procedure Category	72.340	16.802	4.305	0.000
Hour of Operation	0.043	0.032	1.336	0.181
day:Monday	-0.088	0.302	-0.290	0.772
day:Thursday	-0.367	0.319	-1.148	0.251
day:Tuesday	0.123	0.295	0.416	0.677
day:Wednesday	-0.388	0.322	-1.204	0.228
Age	0.028	0.008	3.575	0.000
Body Mass Index	0.003	0.012	0.295	0.768
ASA Physical Status:I-II	8.324	544.450	0.015	0.988
ASA Physical Status:III	9.324	544.450	0.017	0.986
ASA Physical Status:IV-VI	10.301	544.450	0.019	0.985
Charlson Comorbidity Index	0.011	0.035	0.323	0.746

The results of the model in which 30-day mortality is the response variable show that the only statistically significant predictors in the model are the Risk Stratification Index (30-day mortality), the Overall Incidence of 30-Day Mortality for each AHRQ-CCS Procedure Category, and the patient's age. This model shows that after adjusting for critical risk factors, the variability of whether a patient experiences 30-day mortality after a surgical case is not significantly explained by the day of the week or the hour in which the operation took place. In terms of the `hour` of operation coefficient, the model shows that for each additional hour in a workday, the log-odds of a patient experiencing 30-day mortality after an operation are expected to increase by 0.043, holding all other predictors constant. Furthermore, for each additional hour in a workday, the odds of a patient experiencing 30-day mortality after an operation are expected to multiply by a factor of approximately 1.044 (exp(0.043)) holding all other predictors constant. This means that the general odds a patient results in 30-day mortality does increase as the workday day progresses. Since the baseline for the `day of the week` variable is Friday, it is best to interpret the Monday coefficient to gauge the differences between the beginning of the week and the end of the week. The log-odds of a patient having 30-day mortality after an operation are expected to be 0.088 less on Mondays than on Fridays, holding other predictors constant. Furthermore, the odds of a patient having 30-day mortality on Mondays is expected be 0.916 (exp(-0.088)) times the odds of than on Fridays, holding all else constant. This means the odds of a patient having 30-day mortality are a bit lower in the beginning of the week than the end of the week.

Table 2: In-Hospital Complications Model Coefficients/Summary Stats

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-3.420	1.110	-3.081	0.002
Risk Stratification Index (In-Hospital Complications)	0.299	0.016	19.313	0.000
Overall Incidence of In-Hospital Complications for Each AHRQ-CCS Procedure Category	6.250	0.186	33.588	0.000
Hour of Operation	-0.004	0.006	-0.707	0.480
day:Monday	-0.061	0.058	-1.055	0.292
day:Thursday	0.004	0.060	0.065	0.948
day:Tuesday	-0.148	0.059	-2.512	0.012
day:Wednesday	-0.024	0.058	-0.409	0.682
Age	0.011	0.001	8.287	0.000
Body Mass Index	0.009	0.003	3.442	0.001
ASA Physical Status:I-II	-0.338	1.100	-0.307	0.759
ASA Physical Status:III	-0.013	1.100	-0.012	0.991
ASA Physical Status:IV-VI	-0.047	1.103	-0.043	0.966
Charlson Comorbidity Index	-0.004	0.009	-0.391	0.696

The results of the model in which in-hospital complication is the response variable show that the only statistically significant predictors in the model are the Risk Stratification Index (in-hospital complication), the Overall Incidence of In-Hospital Complication for each AHRQ-CCS Procedure Category, the days of the week Tuesday and Friday, the patient's age, and the patient's BMI. This model actually shows that after adjusting for critical risk factors, the variability of whether a patient experiences in-hospital complication is somewhat significantly explained by the day of the week but not the hour in which the operation took place. In terms of the `hour` of operation coefficient, the model shows that for each additional hour in a workday, the log-odds of a patient experiencing in-hospital complication are expected to decrease by 0.004, holding all other predictors constant. Furthermore, for each additional hour in a workday, the odds of a patient experiencing in-hospital complication are expected to multiply by a factor of approximately 0.996 (exp(-0.004)) holding all other predictors constant. This means that the general odds a patient results in in-hospital complication roughly stays the same as the workday day progresses. In terms of the Monday `day of the week` variable, the log-odds of a patient having in-hospital complication are expected to be 0.061 less on Mondays than on Fridays, holding other predictors constant. Furthermore, the odds of a patient having in-hospital complications on Mondays is expected be about 0.941 (exp(-0.061)) times the odds of on Fridays, holding all else constant. This means the odds of a patient having in-hospital complications are slightly lower in the beginning of the week than the end of the week.

Discussion

1) Hour of Operation & 30-Day Mortality

In terms of EDA, the box plots displaying the relationship between the hour of operation and the status of 30-day mortality in Image 15A) show that the patients whose operations result in a 30-day mortality status had operations that took place in hours of a slightly later range than patients whose operations did not result in a 30-day mortality status.(Appendix: Image 15A) Also recalling the *Summary Statistics of Case Frequencies* table above, the distribution of most operations happened in the morning, so it is noteworthy that even though a small proportion of operation cases happened later in the day, they still largely comprised of patients resulting in a 30-day mortality cases in comparison to patients who did not result in 30-day mortality. (Appendix: Image 9) Though the logistic regression model deemed the hour of operation not a statistically significant predictor in the variability of patients' 30-day mortality status, the model still showed that the general odds a patient results in 30-day mortality does increase as the workday day progresses. Overall, this shows that there is an association with the hour of an operation and whether or not a patient results in having 30-mortality. Though this association is not statistically significant, given the context of operations being high stakes and the response variable being a critical measure of ones' life, it is imperative to highlight the relationship found between hour of operation and 30-day mortality.

1) Day of Week & 30-Day Mortality

In the EDA, the bar plots displaying the relationship between the day of the week and the status of 30-day mortality in Image 16A) show slight decreases in the number of patients who do not have 30-day mortality as the week progresses up until Friday.(Appendix: Image 16A) But it is also note worthy that this pattern matches the decrease in the total patient population (Appendix:Image 10) as well as the decrease in percentages of the total patient population as seen in the *Summary Statistics of Case Frequencies* table above. This means the EDA shows there is not a visible relationship between the 30-day mortality status and the day of the week, only the number of patients and the day of the week. The logistic model deemed the day of the week not a statistically significant predictor in the variability of patients' 30-day mortality status but the model still showed there was a slight decrease in the odds of a patient having 30-day mortality as the week progresses. This may be worth noting given the context of this study being a high risk environment.

2) Hour of Operation & In-Hospital Complications

The EDA of Image 15B) shows box plots of the relationship between the hour of operation and the status of patients' in-hospital complications. This image shows that the hour of operations for both statuses take place at relatively the same range of time. (Appendix: Image 15B) This means that there is not a very visible association with the time of operation and whether or not a patient experiences in-hospital complications. The logistic regression model did not express the hour of operation to be a statistically significant predictor in the variability of patients' in-hospital complication status. The model also expressed that the general odds a patient experiences in-hospital complication roughly stays the same as the workday progresses which is reflected in the EDA. Overall, this shows that there is not a noteworthy association between the the hour of an operation and whether or not a patient experiences in hospital complications.

2) Day of Week & In-Hospital Complications

In terms of EDA Image 16B) shows bar plots of the relationship between the day of the week and the status of in-hospital complication. There looks to be a decreasing number of patients without in-hospital complication as the week goes on up until Friday. The visual also shows slight decreases in the number of patients without in-hospital complications as the week progresses besides on Wednesday (Appendix: Image 16B) The pattern in the number of patients without in-hospital complications aligns with the pattern in the total patient population by day of the week (Appendix:Image 10) as well as the pattern in percentages of the total patient population as seen in the *Summary Statistics of Case Frequencies* table above. But the pattern in the number of patients with in-hospital complications among the different days of the week display some differences to the total patient population. This means the EDA shows there is somewhat of a visible relationship between the in-hospital complications status and the day of the week. This aligns with the logistic regression model that shows Tuesday and Friday being statistically significant predictors of the variability of in-hospital complication where the odds of a patient experiencing in-hospital complication is lower on Tuesdays than on Fridays. Overall, this shows that there is a significant associations between the day of the week of the operation and whether or not a patient experiences in hospital complications.

Methodology Evaluation - include accuracy tests of model

Was your methodology fully appropriate? What alternative techniques might have been useful?

- ROC curve
- AUC-PR curve
- Brier score

Limitation

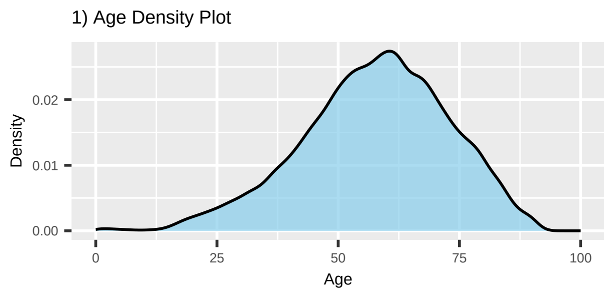
Are there any issues with reliability or validity of the data?

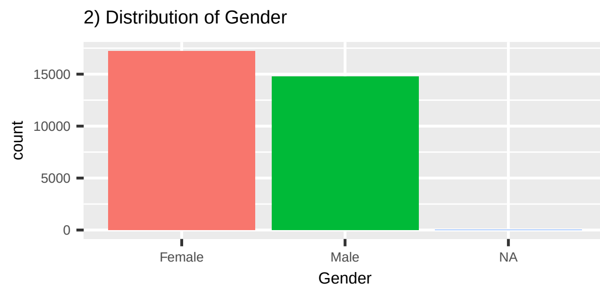
Implications and Conclusions

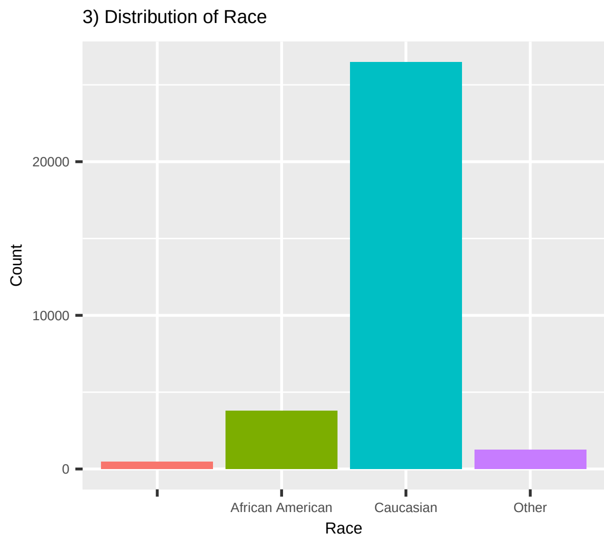
What would you do differently if you had to approach the study again? What additional data sources, variables, or techniques might help you create a stronger manuscript?

Appendix

Extra EDA Visuals







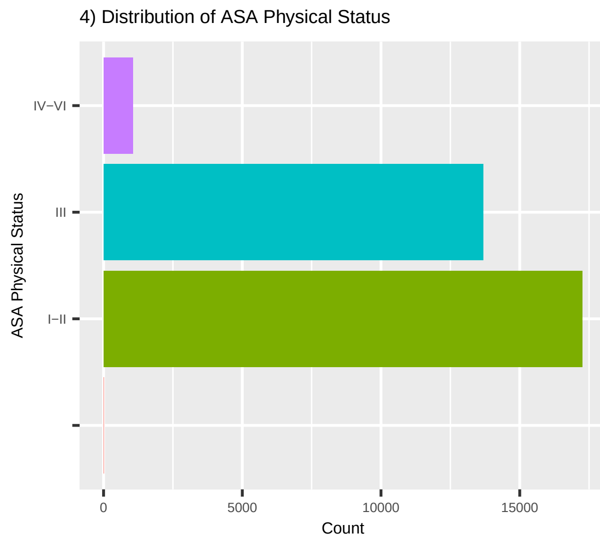


Image 1) Age

Since the distribution of the patients' age is relatively normal and unimodal and not really that skewed to the left the best summary statistic is the mean and the best metric of spread is the standard deviation.

Image 2) Gender

There appears to be a bit more operation cases done on women than men.

Image 3) Race

There are multidude more operation cases done on Caucasian patients than any other racial demographics.

Image 4) ASA Physical Status

*Note: ASA classification uses a grading system of I (one) through V (five) I identifying a person in good health and V as a person with a severe, life-threatening condition. The sixth (VI) status identifies deceased organ donors.

Most patients of operation cases reside in the I-II ASA status and then the III status comes in a close second. There are not many patients that reside in the IV-VI status.

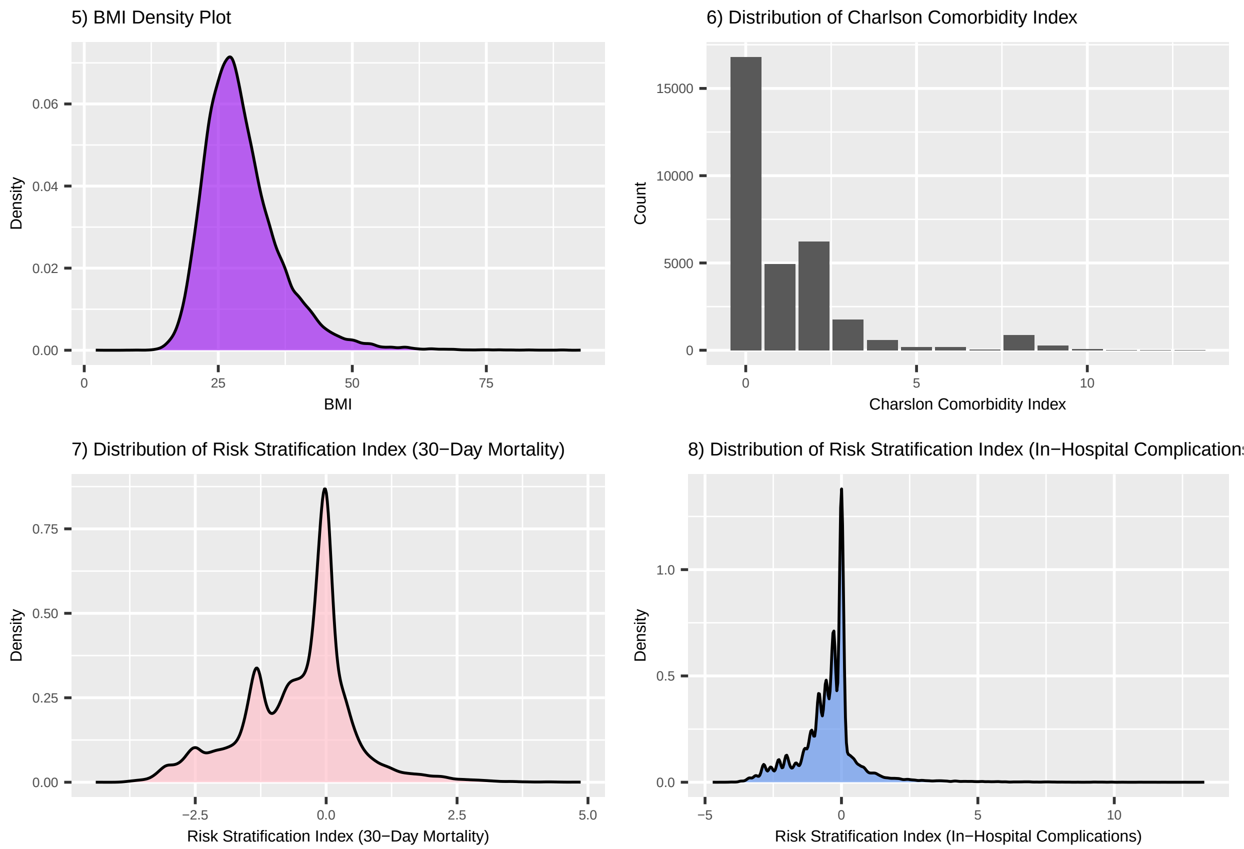


Image 5) BMI

Since the distribution of the patients' BMI is slightly skewed to the right the best summary statistic is the median and the best metric of spread is the IQR.

Image 6) Charlson Comorbidity Index

*Note: The Charlson comorbidity index (CCI) is the most widely used comorbidity index used to determine survival rate (1yr and 10yr) in patient with multiple comorbidities. As the CCI level increases the probability of one year of survival decreases.

Since the distribution of the patients' Charlson Comorbidity Index is skewed to the right the best summary statistic is the median and the best metric of spread is the IQR.

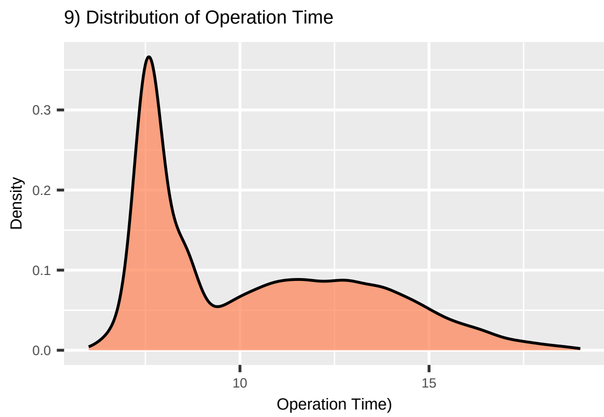
Image 7) Risk Stratification Index (30-Day Mortality)

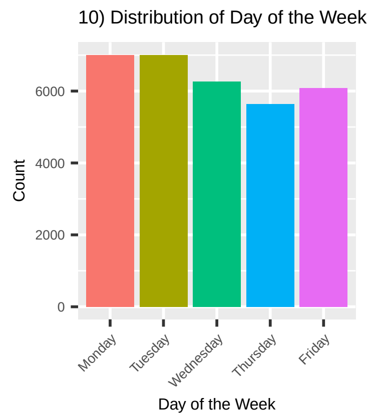
*Note: The Risk Stratification Index (RSI) is an open source, nationally validated, risk stratification methodology that permits outcomes such as duration of hospitalization and mortality to be compared equally across institutions.

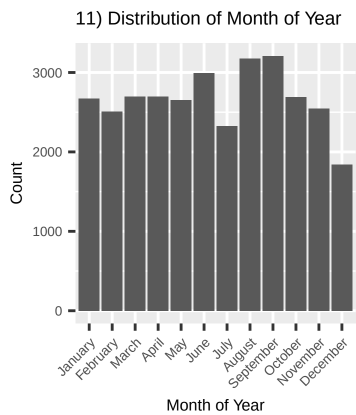
The density chart of the distribution of RSI (30-day mortality) is multimodal and skewed to the left so the median and IQR would be more accurate measures of center and spread.

Image 8) Risk Stratification Index (In-Hospital Complications)

The density chart of the distribution of RSI (in-hospital complications) is multimodal and skewed to the left so the median and IQR would be more accurate measures of center and spread.







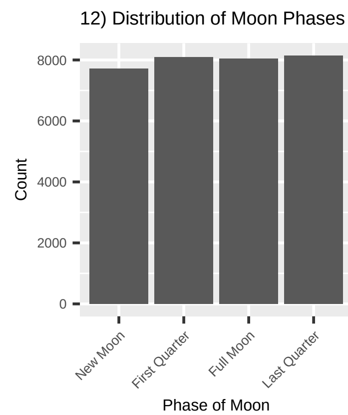


Image 9) Operation Hour

The distribution is bi-modal with a huge concentration of operation hours at around 8:00 am and a much smaller concentration at 12:30 pm.

Image 10) Day of the Week

The distribution of the days the of operation cases tend have a higher concentration in the beginning of the week.

Image 11) Month of the Year

The distribution of the months of operation cases show peaks in June and near the end of the summer (August and September).

Image 12) Phase of Moon

The distribution of the moon phases of operation cases show a relatively uniform distribution with the least cases occuring during new moon phases.

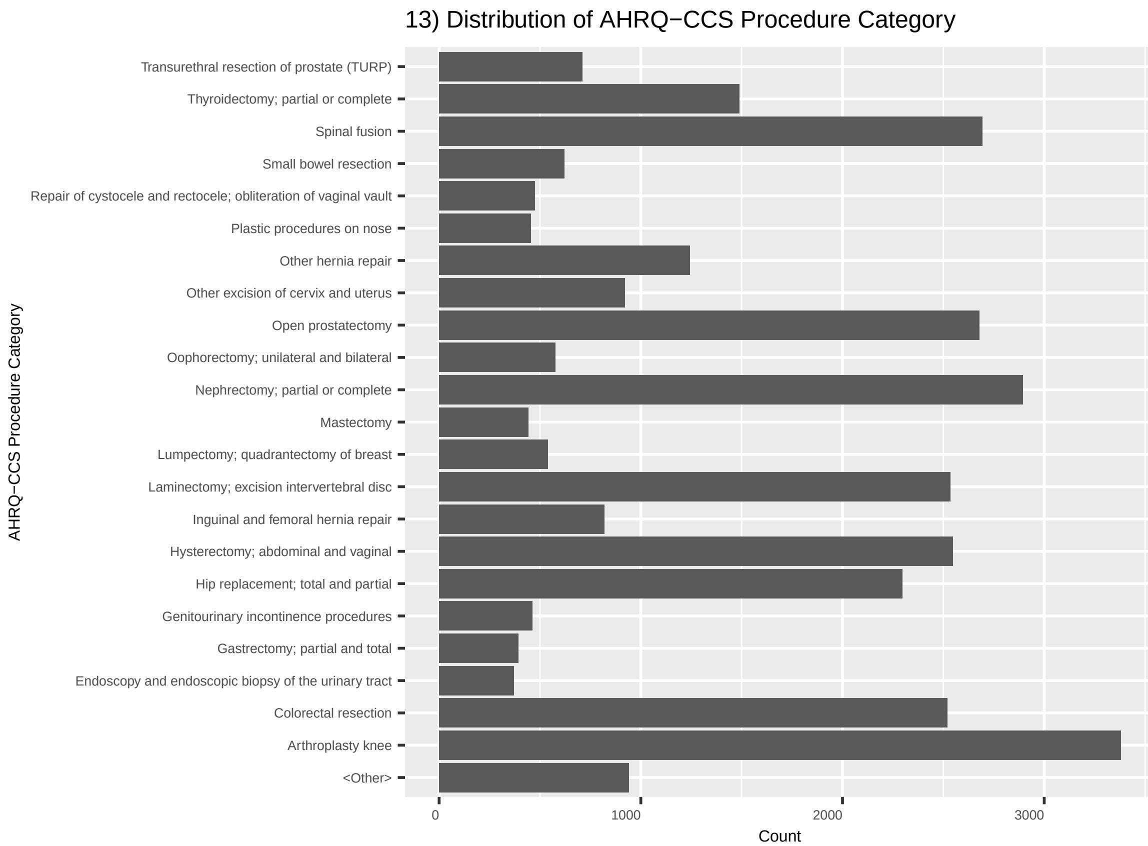
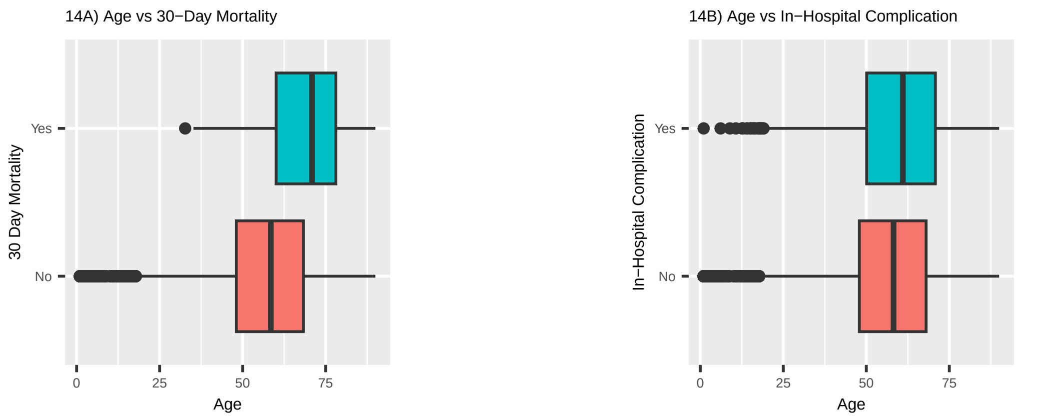


Image 13) AHRQ-CCS Procedure Category

The distribution of procedure type shows there are multiple sporadic procedure types that have very high concentrations of operations and multiple that have low concentrations.



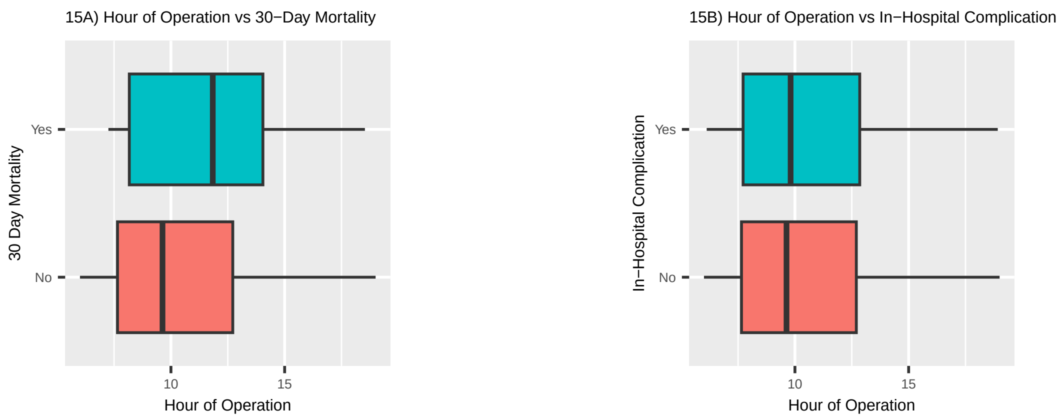


Image 14) Age vs 30 Day Morality and Age vs In-Hospital Complication

The first box plot shows that patients that have 30-day mortality are more generally of an older age than patients who do not have 30-day mortality. The second box plot shows that patients that have in-hospital complications tend to be only slighty older than those who do not.

Image 15) Hour vs 30 Day Morality and Hours vs In-Hospital Complication

The first box plot shows that operations of patients that have 30-day mortality tend to happen later in the day than operations of patients that do not have 30-day mortality. The second boxplot shows that operations of patients that have in-hospital complications tend to be relatively around the same hour in the day as operations of patients that do not have in-hospital complications.

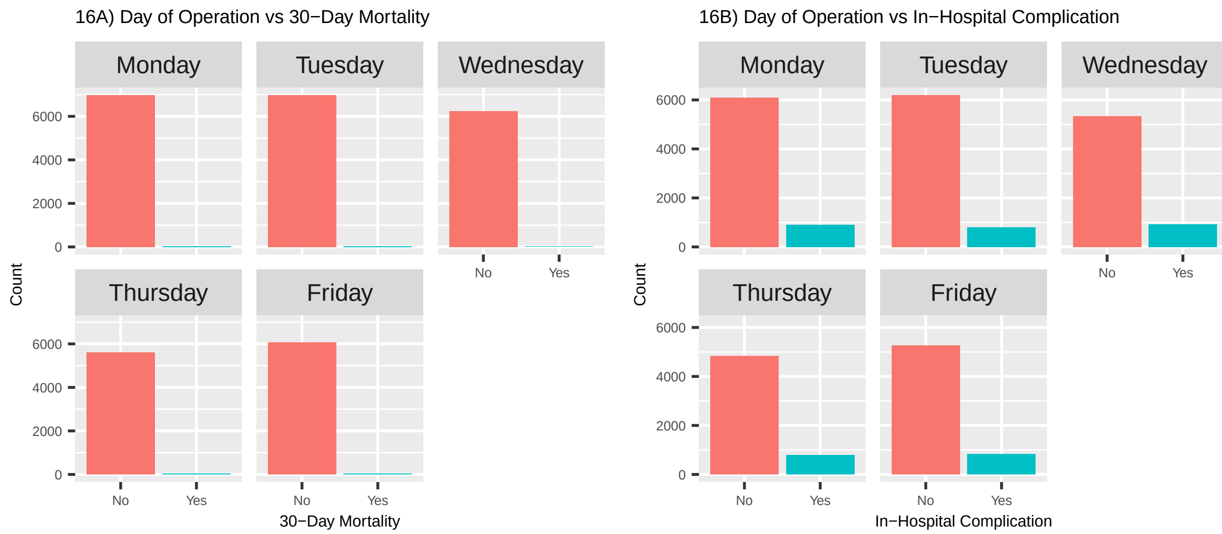


Image 16) Day of Week vs 30 Day Mortality and Day of the Week vs In-Hospital Complication

In bar plot 16A) there is a noticeably decreasing number of patients without 30-day mortality as the week goes on. In bar plot 16B) there is also a decreasing number of patients without in-hospital complication as the week goes on.

Model Diagnostics

Image 17) Linearity: Logit Plot of Hour of Operation vs 30-Day Mortality

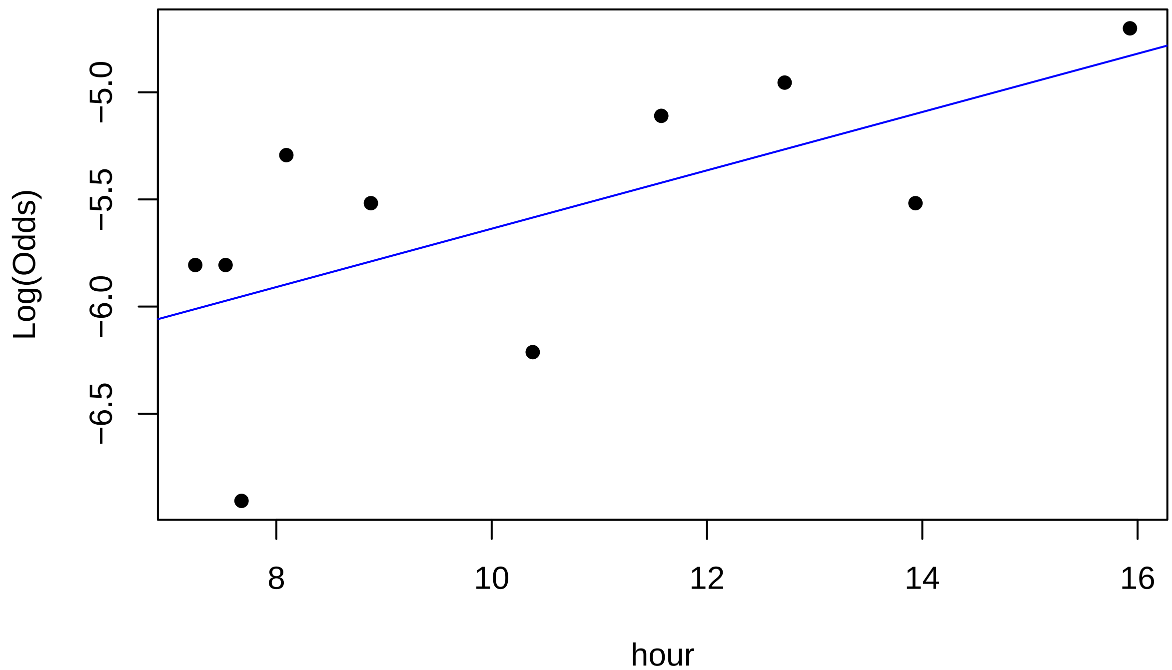


Image 18) Linearity: Logit Plot of Hour of Operation vs In-Hospital Complication

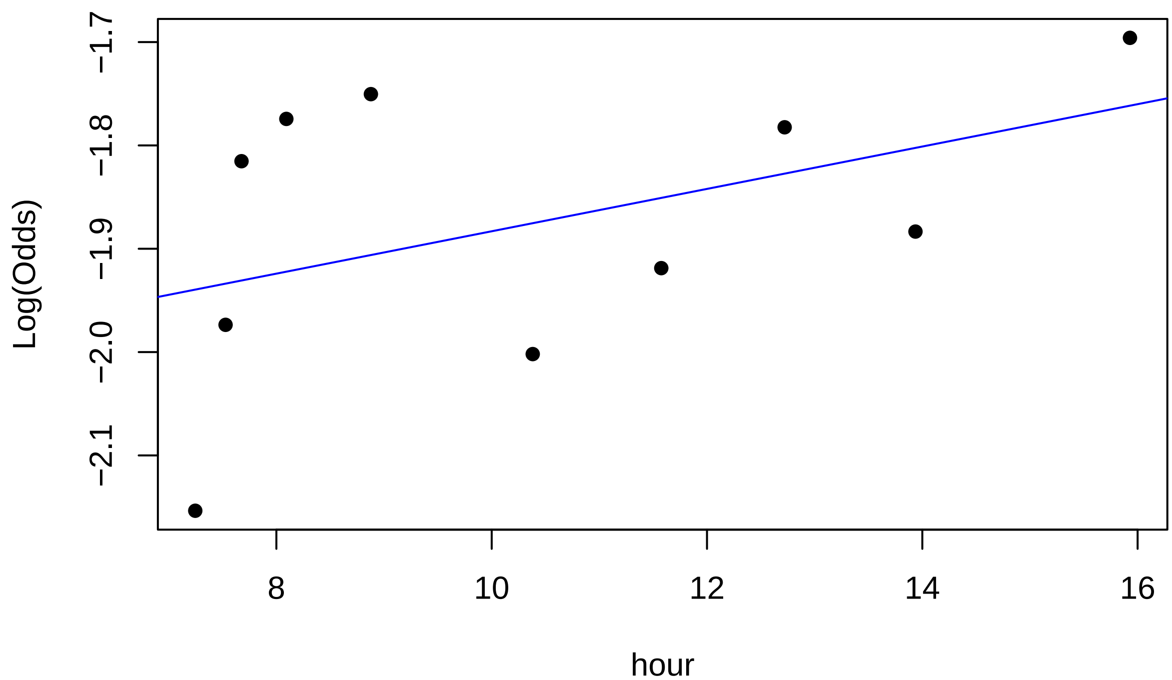


Image 19) Multicollinearity: Correlation Matrix

	mortality_rsi	ccsMort30Rate	hour	age	bmi	baseline_charlson
mortality_rsi	1.000	0.150	0.122	NA	NA	0.254
ccsMort30Rate	0.150	1.000	0.035	NA	NA	0.035
hour	0.122	0.035	1.000	NA	NA	0.027
age	NA	NA	NA	1	NA	NA
bmi	NA	NA	NA	NA	1	NA
baseline_charlson	0.254	0.035	0.027	NA	NA	1.000

Model Accuracy Check

Image 20A) Confusion Matrix and Summary Statistics for 30-Day Mortality Model

```
## Confusion Matrix and Statistics
##
##
## predicted_classes_mort30    0    1
##                        0 5717   19
##                        1    3    2
##
##                Accuracy : 0.9962
##                  95% CI : (0.9942, 0.9976)
##     No Information Rate : 0.9963
##     P-Value [Acc > NIR] : 0.640608
##
##                   Kappa : 0.1527
```

```
##
##  Mcnemar's Test P-Value : 0.001384
##
##             Sensitivity : 0.99948
##             Specificity : 0.09524
##          Pos Pred Value : 0.99669
##          Neg Pred Value : 0.40000
##              Prevalence : 0.99634
##          Detection Rate : 0.99582
##    Detection Prevalence : 0.99913
##       Balanced Accuracy : 0.54736
##
##        'Positive' Class : 0
##
```

Image 20B) Confusion Matrix and Summary Statistics for In-Hospital Complications

```
## Confusion Matrix and Statistics
##
##
## predicted_classes_complication    0    1
##                              0 4897  738
##                              1   49   57
##
##                Accuracy : 0.8629
##                  95% CI : (0.8537, 0.8717)
##     No Information Rate : 0.8615
##     P-Value [Acc > NIR] : 0.3888
##
##                   Kappa : 0.0971
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9901
##             Specificity : 0.0717
##          Pos Pred Value : 0.8690
##          Neg Pred Value : 0.5377
##              Prevalence : 0.8615
##          Detection Rate : 0.8530
##    Detection Prevalence : 0.9815
##       Balanced Accuracy : 0.5309
##
##        'Positive' Class : 0
##
```

Image 21A) Precision-Recall (PR) curves) for 30-Day Mortality Model

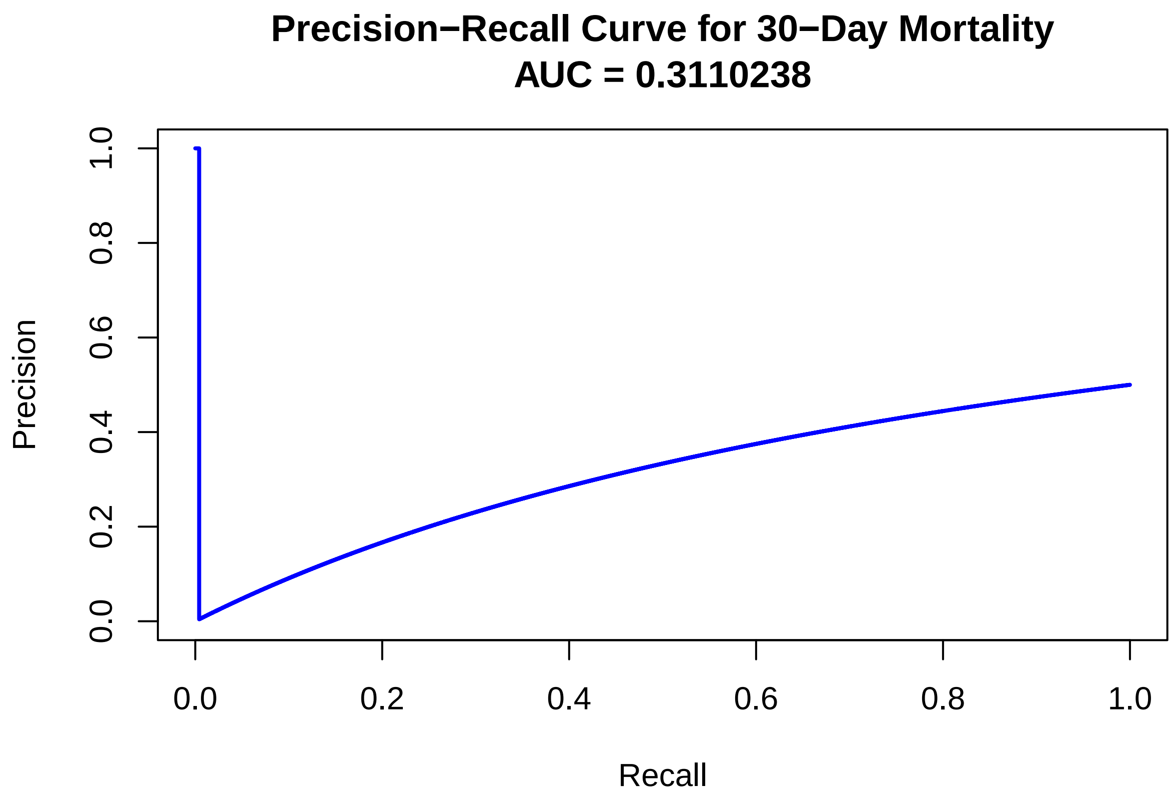
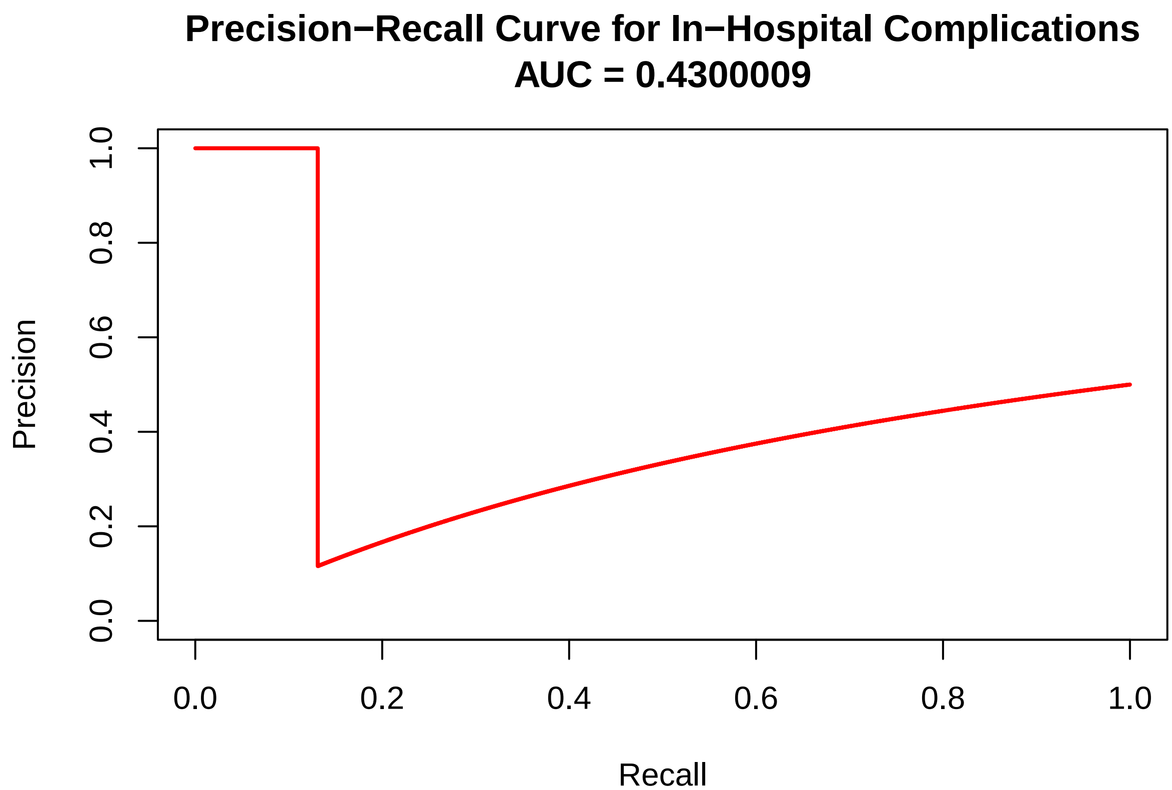


Image 21B) Precision-Recall (PR) curves for In-Hospital Complications



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