# A PREDICTIVE MODEL FOR INPATIENT MAJOR JOINT REPLACEMENT OR REATTACHMENT OF LOWER EXTREMITY

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ABSTRACT OF THE DISSERTATION

A Predictive Model for Inpatient Major Joint Replacement or

Reattachment of Lower Extremity

by FORREST PASCAL

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Many have suggested that the United States healthcare system is broken. Costs are higher than ever, access is limited, and at times quality is questionable. One area of opportunity to lower cost, increase quality, and provide greater access is major joint replacement or reattachment of lower extremity—the most common inpatient surgical procedure for Medicare beneficiaries. Existing research points to emergency department visits, readmissions, and mortality as strong determinants of risk in an inpatient stay for major joint replacement or reattachment of lower extremity. For the current study, approximately 2.3 million inpatient claims were ingested from Medicare, resulting in 74 187 major joint replacement claims being extracted, cleansed, processed, and transformed. For each claim, emergency department visits, readmissions, mortality, and length of stay were calculated, along with the creation of an ICD crosswalk from 9 to 10 and Elixhauser Comorbidity Indexes for mortality & readmissions. A novel algorithm was developed to determine the risk of each claim. SAS Enterprise Miner, MATLAB, and MLJAR were used to mine the claims using supervised machine learning algorithms, and Tableau was used to visualize correlations and create 2D plots. This research provided the following insights: Matlab's Ensemble Boosted Tree algorithm

predicted the novel risk 8.out of 10 times across both the training and test dataset, proving its portability and reliability. Consistently, the physicians, provider (hospital), claim payment, type of admission and beneficiary county yielded the strongest predictor strength in predicting the outcome novel risk derived from emergency department visits, mortality, and readmissions. These predictors present areas of opportunity to lower cost, increase access, and improve quality by being used as indicators for early warning & surveillance systems for case workers, clinicians, and hospital administrators. Furthermore, machine learning models utilized in value-based care can assist healthcare leaders, payers, and providers with decision making on which care models may be most effective in facilitating associations to data on outcomes about patients with the highest risk profiles—specifically to identify which patients to follow more closely, which physicians and hospitals have the most successful results, and which geographic areas have differing results. Additionally, white females made up over 60% of observations, and both white females and males had the costliest claim payments. Lastly, obesity and hypertension (complicated & uncomplicated) were the most frequent comorbidities across gender, race and age group.

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It is with my deepest gratitude that I pay tribute to my committee chair, Associate Professor Shankar Srinivasan. His unwavering commitment to my success both within and outside of this program must not go without mention. I am eternally grateful and have truly been blessed with such a beloved colleague and mentor. Further thanks are in order to my committee members: Assistant Professor Suril Gohel, for his steadfast availability and tireless assistance with MATLAB, which gave me the confidence to use it in this work; Dr. Erica Strandberg, whose expertise in Biomedical Informatics and Statistics, as well as her position as Executive Director for Data Science & AI initiatives at Stanford University, lend credence to this work; and Dr. Tamara Cull, Senior Vice President at Medecision and subject matter expertise with anything Medicare, for contributing her knowledge to make this exploration meaningful. Further acknowledgement must be given to the Center of Medicare and Medicaid Services, for entrusting and granting me access to Medicare claims data; to ResDAC, for their guidance in acquisitioning and understanding Medicare data; and to the technical support team at SAS Institute—especially Michael Stockstill. Kudos also to MATLAB technical support, who spent countless hours with me in guidance, support, and tutelage.

This acknowledgement would not be complete without honoring my mother, who only had a 3rd grade education and whose family had no one in it who ever been past the 11th grade. As a child, she would get up at 4 am in the morning, wash and dry her only dress in a wood burning oven, and then walk 9 miles each way to school. Education was important to my mother, and she always dreamed of graduating from high school and college; but she never got the chance to achieve her

dream, as one morning, that dress burned up in the oven along with her opportunity to continue going to school. In spite of that setback, she never lost hope or her understanding that education was an equalizer and key to dreams. She worked cleaning homes during the depression for 9 cents an hour and saved every penny that she had to provide a life for me and instill that message of hope through education. It is this resounding message, instilled in me by my mother, that deserves mentioning. Last but not least is the recognition of my wife, who earned this degree alongside me. Not only did she clear my plate of the mundane duties of home life, enabling me to focus on this regal achievement; she also placed her faith, hope, and joy in the transformative power of achieving the title bestowed by this esteemed university—Doctor of Philosophy.

This paper is dedicated to the gracious throne of the Almighty God through His Son Jesus Christ, Who has given me the strength to complete this work

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# CHAPTER I
# INTRODUCTION

## 1.1 Background

Health care access, cost, and quality in the United States have been in constant turmoil, flux, and change. This issue has persisted since the early 20th Century, when Theodore Roosevelt campaigned in 1912 on the creation of a health insurance plan for all Americans. Roosevelt was, however, unsuccessful in his bid for President, and the cry for a national health insurance plan fell silent until the topic resurfaced with President Harry Truman, whose efforts too fell short.[1] President John F. Kennedy took up the issue and once again was unable to succeed where other presidents had failed, even though studies showed that more than half of Americans over the age of 65 had no health coverage.[1] It wasn't until 1965 that President Lyndon B. Johnson was able to sign into law a national health care benefit for those over the age of 65 called Medicare.[1] Fast forward to 2008 when the first black President of the United Stated was elected, Barack Hussein Obama—who was in his first term able to secure nationwide insurance coverage for everyone amid heavy opposition. Today, Obama's legislation—officially known as the Patient Care and Affordable Care Act (PCACA)—is more widely known as Obamacare.[1] Pertinent to this study was the creation of the Center for Medicare and Medicaid Innovation (CMMI) under the Affordable Care Act, which was chartered with researching and developing innovative payment models to address access at a reduced cost while

maintaining or improving quality. These models are piloted on a limited basis with hospitals and providers and monitored for their effectiveness, with the possibility of being put into law for nationwide adoption.[2] Obamacare has been repealed and for the most part dismantled, leaving the health care industry still searching for a solution that will lower cost, increase access, and improve on quality. Hence, America's health care system future is uncertain as it relates to resolving cost, access, and quality issues.

While the debate on Medicare and Obamacare can still be heard from barbershops to coffee shops, and throughout the halls of congress, Americans from all walks of life are sounding off over concerns of out-of-control health care costs, limited access to health care, and questionable quality of care. It can be said that Americans are again being faced with the dilemma of a health care depression, due in part to the high monthly cost for individuals and families to keep health insurance. There are too many cases where families must choose between health care coverage and basic essential living expenses like housing and food. An area of hope and opportunity for decreased cost, enhanced access, and improved quality is major joint replacement (MJR) or reattachment of lower extremity, which comprise the most common inpatient surgical procedure performed on Medicare beneficiaries.[3] These are surgical procedures to replace joints below the waist that are also referred to as total joint arthroplasty (TJA). The definitions of major joint replacement or reattachment of lower extremity are captured in Table 32 in Appendix A.[4] Regarding this study, the primarily focus will be on ankle, hip, and knee replacement.

Arthroplasty is performed in several ways; joint resection, interpositional reconstruction, and joint replacement. The surgical procedure is usually an

imperative for patients with osteo- or rheumatoid arthritis, and is in most cases required for patients who are 60 years of age and older or whose bone and socket are damaged.[5] Recovery and rehabilitation are costly and can require long rehab periods. As of 2014, the number of lower extremity joint replacements had exceeded 400 000 procedures totaling $7 billion dollars for inpatient stays. Notwithstanding the high number of these procedures, cost and quality variance were high amongst providers. Furthermore, infection and implant failure after the procedure have seen in some cases a threefold increase, significantly raising the odds of readmission. Additionally, the average Medicare cost for the procedure ranges from $16 500 to $33 000.[3] TJA procedures are projected to reach 4 million by 2030 from their current total of 2.3 million, according to one estimate—this is a whopping 174% increase.[6] Because of the prevalence of these procedures and the widespread impact they have on many patients' lives, this study aims to uncover predictors of risk in an inpatient surgical stay for MJR or reattachment of lower extremity other than the known risk determinants of unplanned readmissions, emergency department visits, and mortality.

During this exploration, inpatient claim data for MJR or reattachment of lower extremity were flagged as questionable risk if the claim contains one or more emergency department visit or readmission and if the claim indicates the patient died, or as acceptable risk if no emergency department visits, readmission, or mortality exist. Thereafter, this dataset was mined for other predictors that are important in predicting the questionable risk value in the novel risk flag. The surgical procedures under test were captured as medical severity diagnosis-related groups (MS-DRG), as listed below:

- MS-DRG 469: Major Joint Replacement or Reattachment of Lower Extremity with Major Complications and Comorbidities (MCC)
- MS-DRG 470: Major Joint Replacement or Reattachment of Lower Extremity without Major Complications and Comorbidities

## 1.2 Problem Statement

Major joint replacement or reattachment of lower extremity, as already stated, is the most common inpatient surgery performed on Medicare beneficiaries. Gaining additional insight into ways to reduce cost, open up additional access paths to care, and improve quality could potentially benefit millions. The principal motivation behind these objectives is getting the right information into the right hands at the right time in order to make the right decision. The use of machine learning modeling rather than statistical modeling provides the portability and reusability of the model to a new dataset without additional programming. Thus, the central challenge being pursued is to develop a predictive machine learning model based on independent variables found in Medicare inpatient claim data, where the model is highly accurate in predicting a risk-based dependent variable outcome using a set of known independent variables of unknown predictive strength without knowing the associations and correlations among the independent variables.

Research conducted by Dummit et al[7] into inpatient stays for lower extremity joint replace (LEJR) show an association with emergency department visits, mortality, and readmission through the use of statistical tests. These tests describe the relationship between variables in the form of summary statistics, central tendency, distributions, associations, correlations, and statistical predictive models using mathematical formulas on a single set of data. Furthermore, the machine

learning models generated from their research can be used on this data, and thereafter the same model can be used on subsequent datasets with the same data attributes and characteristics (supervised machine learning). Hence, machine learning learns from its data without having to involve additional formulas and programming. Figure 1 shows a Venn diagram illustrating the interrelationship between statistics, machine learning, pattern recognition, data mining, knowledge discovery and databases (KDD), artificial intelligence (AI), and neurocomputing.[8]

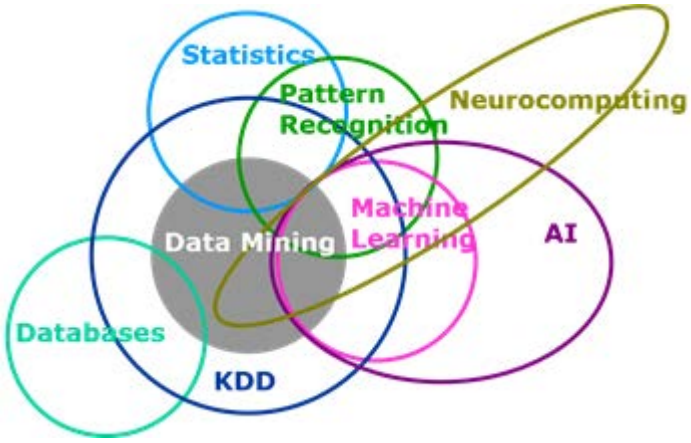



**Figure 1.** The Interrelationship between Data Mining and Adjacent Fields

A library search using the Rutgers George F. Smith QuickSearch tool[9] of varying combinations of the search terms "data mining" and "machine learning" with "lower extremity joint replacement," "major joint replacement," and "DRG 469/470" yielded not a single peer-reviewed article addressing the use of machine learning models used on inpatient claims data for major joint replacement or reattachment of lower extremity. The lack of results provides the evidence of a clear gap in research in this area. Results were found authored by Navarro et al[10] and Ramkumar et al[11] when using the search criteria "machine learning" and "arthroplasty." However, not a single peer-reviewed article from any of the search results used Medicare inpatient claims data.

## 1.3 Significance

Previous literature has already proven associations of risk for inpatient stays in MJR or reattachment of lower extremity with emergency department visits, readmission, and mortality.[7] However, discovering more about the relationship between other independent variables that influence these known risk factors would provide better quality and possibly reduce risk by providing insight to case workers and clinicians when assessing patient risk throughout the clinical pathway for lower extremity joint replacement.

## 1.4 Research Purpose

The purpose of this study is to determine the accuracy of other predictors or determinants of risk for MJR or reattachment of lower extremity surgical procedures DRG 469 & 470 within the inpatient claims data that are determinants of emergency department visits, mortality and readmissions. The independent variables that will considered are listed in Table 1. The dependent variable is defined as high or low Risk. The participants are Medicare beneficiary patient claim records captured during inpatient stays from 2013 to 2016 at acute hospital facilities.

An exploratory data analysis (EDA) approach has been used to gain an understanding of the connections among variables using statistical tests. Understanding these connections contributes to obtaining a clearer picture of the variables' relationships through the generation of summary statistics of the data, the distribution of the variables, and their associations using logistic regression. The results of these statistical tests and analyses will help to better determine which machine learning algorithms best fit specific binary classification problems.

**Table 1.** Independent Variables

| Category | Variable |
|---|---|
| Access | provider |
| | provider state |
| | attending physician |
| | operating physician |
| | organization physician |
| | beneficiary state |
| | beneficiary county |
| | age group |
| | race |
| | gender |
| | source of admission |
| | type of admission |
| Comorbidities | congestive heart failure |
| | valvular disease |
| | pulmonary circulation disease |
| | peripheral vascular disease |
| | hypertension-crisis |
| | paralysis |
| | other neurological disorders |
| | chronic pulmonary disease |
| | diabetes without chronic complications |
| | diabetes with chronic complications |
| | hypothyroidism |
| | renal failure |
| | liver disease |
| | peptic ulcer disease with bleeding |
| | hypothyroidism |
| | acquired immune deficiency syndrome |
| | lymphoma |
| | metastatic cancer |
| | solid tumor w/out metastasis |
| | rheumatoid arthritis |
| | coagulopathy |
| | obesity |
| | weight loss |
| | fluid and electrolyte disorder |
| | chronic blood loss anemia |
| | deficiency anemias |
| | alcohol abuse |
| | drug abuse |
| | psychoses |

**Table 1.** Continued

| Category | Variable |
|---|---|
| Cost | payment amount |
| Utilization | drg |
| | drg outlier stay |
| | drg weight |
| | length of stay |
| | elixhauser readmission risk |
| | elixhauser mortality risk |
| | elixhauser readmission index score |
| | elixhauser mortality index score |

## 1.5 Research Question

The research question sought to answer this central question: Are there independent variables (IV) significantly associated with the dependent variable novel risk?

## 1.6 Research Hypotheses

It is hypothesized in MJR cases that predictive models can be developed using machine learning techniques for surgical DRG 469/470 outcomes based on patient-related data collected in Medicare inpatient claims. The hypotheses are classified as follows:

- ✗ Null Hypothesis: $H_0$ = Is not a significant predictor of the novel risk in the selected model
- ✓ Research Hypothesis: $H_1$ = Is a significant predictor of the novel risk in the selected model.

## 1.7 Assumptions

There is a lack of research using statistical machine learning to mine Medicare MJR or reattachment of lower extremity inpatient claim data for

predictors of risk. While there are several well-known determinants associated with risks for readmission, emergency department visit, and mortality—e.g., claim payment amount, length of stay, comorbidities, etc. in an inpatient stay[7]—the aim of this research is to unearth other determinants of these three specific risks in an inpatient stay. Furthermore, there exists a gap in the literature of research studies demonstrating the use of machine learning algorithms in finding other determinants of risk in an inpatient stay other than those previously named or well known. Therefore, the objective of this research is to use classification algorithms (excluding the known predictors formerly mentioned) to assess if other determinants can predict the novel risk—qualifying them as predictors of readmission risk, emergency department visit risk, and mortality risk for MJR or reattachment of lower extremity.

## 1.8 Limitations

The research only uses Inpatient Limited Data Sets (LDS) for the years 2013-2016. These datasets only contain 5% of the inpatient claim data for each year. Hence, recreation of a complete episode of care or bundle cost is not possible. Additionally, in the Inpatient LDS claim data, there is no variable for the claim start date, hindering the reconstruction of an entire episode of care for each beneficiary claim record.

## 1.9 Definitions

| | |
|---|---|
| ACCI | Age-Adjusted Charlson Comorbidity Index |
| AI | Artificial Intelligence |
| AIC | Akaike Information Criterion |
| APM | Alternative Payment Model |
| ASE | Average Squared Error |
| BPCI | Bundled Payment for Care Improvement |
| CCI | Charlson Comorbidity Index |
| CCJR | Comprehensive Care for Joint Replacement |
| CCS | Combined Comorbidity Score |
| CM | Clinical Modification |
| CMS | Center for Medicare and Medicaid Services |
| CMMI | Center for Medicare and Medicaid Innovation |
| CP | Clinical Pathway |
| CSV | Comma Separated Value (File Type) |
| CV | Cross Validation |
| DF | Degree of Freedom |
| DJD | Degenerative Joint Disease |
| DRG | Diagnosis Related Group |
| DVT | Deep Vein Thrombosis |
| DV | Dependent Variable |
| ECI | Elixhauser Comorbidity Index |
| EDA | Exploratory Data Analysis |
| EG | Enterprise Guide |
| EM | Enterprise Miner |

| | |
|---|---|
| ER | Emergency Room |
| FDR | False Discovery Rate |
| FFS | Fee-for-Services |
| FSCNCA | Feature Selection Classification Neighborhood Component Analysis |
| FPR | False Positive Rate |
| HCC | Hierarchical Condition Category |
| H-CUP | Healthcare Cost and Utilization Project |
| HP BN | High-Performance Bayesian Network Classifier Node (SAS) |
| ICD | International Classification of Diseases |
| IV | Independent Variable |
| IPPS | Inpatient Prospective Payment System |
| KDD | Knowledge Discovery and Databases |
| KL | Kellgren and Lawrence Score |
| KNN | K-Nearest Neighbor |
| LDS | Limited Data Set |
| LEJR | Lower Extremity Joint Replacement |
| LOS | Length of Stay |
| LR | Logistic Regression |
| MCC | Major Complications and Comorbidities |
| MFI | Modified Frailty Index |
| MISC | Misclassification Rate |
| MJR | Major Joint Replacement |
| MS-DRG | Medical Severity Diagnosis Related Group |
| NCA | Neighborhood Component Analysis |
| NIS | National Inpatient Sample |

| | |
|---|---|
| NYULMC | New York University Langone Medical Center |
| OOB | Out-of-the-Box |
| PAC | Postacute Care |
| PCA | Principal Component Analysis |
| PCACA | Patient Care and Affordable Care Act |
| PCS | Procedure Coding System |
| PFP | Pay for Performance |
| PHI | Protected Health Information |
| PLOS | Prolonged Length of Stay |
| PPV | Positive Predictive Values |
| RDOA | Rapidly Destructive Osteoarthritis |
| ROC | Receiver Operating Curve |
| SAS | Statistical Analysis Software |
| SC | Schwarz Criterion |
| SD | Standard Deviation |
| SNF | Skilled Nursing Facility |
| SVM | Support Vector Machine |
| THA | Total Hip Arthroplasty |
| TJA | Total Joint Arthroplasty |
| TKA | Total Knee Arthroplasty |
| TPR | True Positive Rate |
| UDMT | Unified Data Mining Theory |
| VBP | Value-Based Program |
| VTE | Venous Thromboembolism |

# CHAPTER II
# LITERATURE REVIEW

Kissick's Iron Triangle of Health Care[12] (see Figure 2) describes the cause and effect of the health care triple constraint: (1) a proportional increase or decrease in access proportionally effects cost and quality; (2) a proportional increase or decrease in cost proportionally effects access and quality; and (3) a proportional increase or decrease in quality proportionally effects access and cost. This literature review is an exploration into access, cost, and quality and their effects on major joint replacement (MJR) or reattachment of lower extremity, using the Iron Triangle as the overarching framework for increasing access, lowering cost, and improving quality for major joint replacement or reattachment of lower extremity.

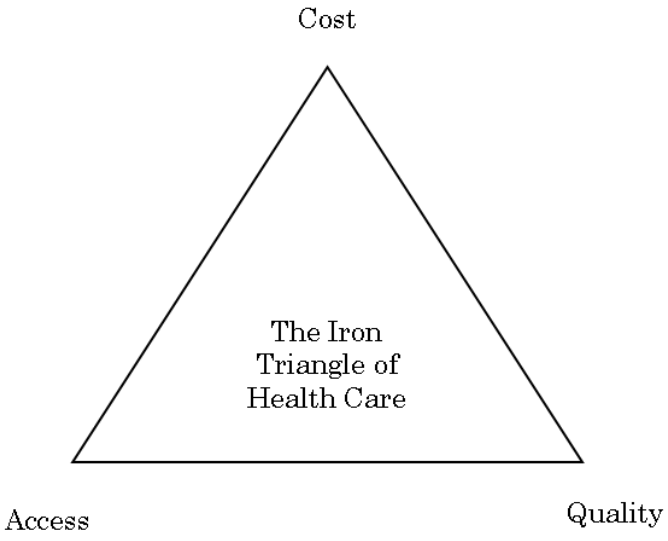



**Figure 2.** The Iron Triangle of Health Care

## 2.1 Access

According to McConnell et al,[13] the prevalence of major joint replacement or reattachment of lower extremity procedures over the next 8 years is expected to increase. Demand is expected to increase 170% for hip replacement and 600% for knee replacement. As of 2015, total knee arthroplasty's in America was well past one million—double the number of total knee arthroplasty's in the previous 10 years—and as a result, Medicare became the largest funder of arthroplasty. Over the past 15 years, however, there has been considerable racial disparity with African American major joint replacement or reattachment of lower extremity patients compared to white patients, with the utilization for African Americans being 41.5 per 10 000 as compared to 68.8 per 10 000 for whites. When set side by side with white patients, African Americans have a low affinity for the treatment, and in general, non-white patients frequent lower quality hospitals, resulting in arthroplasty outcomes that include higher rates of hospital readmission. Additionally, disparity was found with African American patients and rehabilitation care. The study further showed race as being strongly correlated with where the patient is discharged after the procedure; African Americans had higher odds of admission to a skilled nursing and inpatient rehabilitation facility when under 65 years old following the procedure, and higher odds were also associated with readmission to hospitals.[13]

Disparity emerges as a significant theme. The Comprehensive Care Joint Replacement (CCJR) program of Medicare took note that the program causes an adverse effect on disparity through a lower access to poor black patients than affluent black patients.[13] In an effort to aid African American patients in decision making regarding total knee arthroplasty, a clinical trial was conducted by Ibrahim

et al[14] to determine whether decision aids and counseling would raise the adoption rate in African Americans to undergo total knee arthroplasty (TKA). The compelling reason to conduct this study is that African American patients, far more than white patients, choose not to have the procedure done. It was concluded that decision aids do increase the adoption rate for African American patients to undergo TKA.[14] In a related study, Kim et al[15] studied patient access to the procedure across several states, and it was found that patients insured by Blue Cross had no problem making an appointment for TKA, and in most cases, Medicare patients had no problem making an appointment either. Medicaid patients, however, were not able to make appointments.[15] Further examining the disparity in access to total hip and knee arthroplasty, Hawkins et al[16] analyzed patients within a Medicare supplement plan from UnitedHealthcare using regression analysis across age, sex, race, and income characteristics, and it was found that males were more likely than females to have a lower extremity arthroplasty, that low socioeconomic status decreased the chances of receiving lower extremity arthroplasty, and that the type of Medicare gap insurance was a weak predictor of lower extremity arthroplasty. Additionally, disparity was strong when a comorbidity existed, and was also correlated to demographic and income status.[16] Therefore, these results show the viability of outpatient total knee arthroplasty as a means to lower cost and increase access for Medicare patients while maintaining a high level of quality.[16] Demographic information is already known as having a strong association to access variables and will play a predictive role in this research.

## 2.2 Cost

When reviewing cost as a determinant of risk for emergency department visits, mortality, or readmission in an inpatient major joint replacement or reattachment of lower extremity in a claim, one must also look at the claim payment and total charges on the claim. However, total charges will be omitted as a predictor, as all the charges in the claim record cannot be verified as being related to the MJR surgical procedure. Therefore, the claim payment will be the central focus of the cost literature. With that said, Boylan et al[17] assessed the strength of the Comprehensive Care for Joint Replacement (CCJR) model at lowering cost and length of stay. The study looked at ankle, hip, and knee arthroplasty and surmised that ankle arthroplasty cost was higher at time of admission then hip and knee arthroplasty; however, average length of stay for ankle arthroplasty was less.[17] Brewer[18] further evaluated cost-related effects of the CCJR and its regulatory impact on providers, Medicare, and fraud. Specifically, the study considered the impact of fraud by providers referring to providers, thereby creating an atmosphere of cronyism while lowering cost. In this case, lower cost may actually result in driving up cost due to the low quality being created by this network of providers.[18] Therefore, there is a likelihood of cost and providers being predictors of risk in major joint replacement or reattachment of lower extremity.

Additionally, there is literature (e.g., Cohen et al[19]) suggesting that the cost for Medicare patients with pre-existing conditions cannot be lowered during arthroplasty unless there is a presurgical intervention,[19] as well as literature suggesting total knee arthroplasty on Medicare patients be performed as an outpatient procedure. One such study by Courtney et al[20] sought to determine if the procedure is cost-effective. The authors found that complications were down when

there was at least a one-day stay after arthroplasty. Of note is that the patients with one-day inpatient stays after arthroplasty had the same complication occurrence as those who had the regular inpatient procedure.[20] There may, therefore, be positive implications in using length of stay as a determinant of risk, as well as further evidence that reduced cost is an outcome of longer stays. A separate study by Courtney et al[21] examined whether hospitals with higher volume had a lower cost for hip and knee surgery than low volume hospitals. The researchers asked that, if so, might adopting their methods lower the cost for the low volume hospitals? In their analysis, Medicare data was used for DRG 470, and postsurgical complications were considered. The results did indicate that low volume hospitals could lower cost by taking on the best practices of higher volume hospitals, suggesting that provider may be a determinant of lower cost—which may further indicate a lower risk level.[21]

In another study by Culler et al,[22] complications related to major joint replacement or reattachment of lower extremity for Medicare patients were studied, as well as the costs associated with those complications. By parsing Medicare data by eight complication types, it was found through the Fisher exact test that cost is a determinant of the complication type, suggesting that complication type is a strong determinant of risk.[22] In another study, Lovald et al[23] examined cost, outcomes, and mortality for total knee arthroplasty in Medicare patients. There were two groups: surgical and nonsurgical. Costs were higher for the surgical group than nonsurgical group; however, the surgical group had a lower mortality rate and heart failure occurrence. This evidence is a strong case for cost as a determinant of risk.[23] When considering payment types, episode-of-care and fee-for-service (FFS) are the predominate forms of Medicare payment. One study by Middleton et al[24] looked to

determine if payment type had an impact on cost and quality, complications, and mortality for major joint replacement or reattachment of lower extremity. The study further looked to understand the impact of outcomes when lined up against other payment types in ninety days. It was found that the occurrence of pneumonia had the highest frequency of complication and the payment type did not come into play in a significant way when regarding costs and quality. Thus, payment type is not considered as a predictor; complications, however, were present in DRG 469.[24]

Ellimoottil et al[25] studied the billing process for major joint replacement or reattachment of lower extremity using Medicare's CCJR program as the payment framework. The objective of the study was to evaluate the episode of care in DRG 469 & 470 procedures. There were no significant results from the study,[25] suggesting that payment and the type of episode of care may not be significant determinants of risk. Regarding CCJR and payment, Markov Cohort model was used by Koenig et al[26] to evaluate four groups of Medicare patients' spending and patient outcome of total hip arthroplasty within the context of CCJR. It was found that desire to pay strongly correlates to cost outcome.[26] Furthermore, the inquiry by Maniya et al[27] into major joint replacement or reattachment of lower extremity investigated the strength of hospitals' desire to shift their payment methods and practices to accommodate the CCJR. Their findings showed that hospitals preferred practices that were either void of action, placed less emphasis on care, placed more emphasis on care, or put heavy care emphasis with contracting. This study did not find a correlation between the CCJR program's payment methods and lower costs for major joint replacement or reattachment of lower extremity.[27]

A study conducted by Navathe et al[28] questioned whether there are unforeseen outcomes related to the Medicare cost reductions for providers who

participate in the CCJR program. The study hypothesized that cost is not lowered for providers when volume is increased for major joint replacement or reattachment of lower extremity. As a result, the researchers advocated transparency across access to hospitals, cost, and quality in the CCJR program.[28] Elsewhere, Navathe et al[29] examined the CCJR program to understand the impact bundled payment had on quality, postacute care, and costs for major joint replacement or reattachment of lower extremity patients. What was found is that costs, readmissions, prolonged length of stay (PLOS), and emergency room visits all trended down, whereas complications did not change. Also, of note is the finding that the bundled payment model did lower spending.[29]

There is a wealth of literature regarding bundled payments, cost, and associated risk factors. A study by Courtney et al[30] investigated whether patients who undergo major joint replacement or reattachment of lower extremity using Medicaid would benefit from a bundled payment method. They also sought to answer whether the cost was higher than private insurance and Medicare. It was found that Medicaid patients' costs were higher than private insurance and Medicare. There was a direct correlation between cost, LOS, and comorbidities. This gives high probability that LOS and comorbidities are a strong determinant of risk.[30] Concerning cost and readmissions, providers in Model 2 and Model 3 of the Bundled Payments for Care Improvement (BPCI) program compared the cost-effectiveness of major joint replacement for lower extremity Medicare patients. It found that both providers realized cost savings: Model 2 cost savings were realized through reduced readmissions and Model 3 through shorter lengths of stay and lower readmissions.[31] Also, in 2015, Cull[32] put to test the covalency between cost and readmission for Medicare patients undergoing major joint replacement or

reattachment of lower extremity with several hospitals associated with a large hospital group. The study examined BPCI Phase 1 and 2 participants. It was found that total cost did decrease for Phase 2 participants and was $3333 per episode lower than participants in Phase 1. Regarding readmission rates, neither phase showed a decrease or increase.[32]

According to Froemke et al[33], by 2030 the number of total joint arthroplasty (TJA) procedures performed are projected to skyrocket to four million from the current total of 2.3 million, according to one estimate—this is an astounding 174% increase.[33] Out of all clinical procedures, TJAs have the least standardization across operative care and payment, exposing the inefficiencies and lack of quality in the FFS payment model. Enter into this an alternate payment model that shifts the paradigm from FFS to episodes, where reimbursements for an episode of care are bundled into one payment dispersed by the hospital to all providers of service, with incentives based on quality. This shifts the focus for the providers to delivering quality consistently across episodes at an affordable cost with opportunity to gain a larger payout based on the quality of the care delivered.[34]

One can find evidence that BPCI enhances care and reduces costs associated with waste and variation in treatment, but there exists a gap in the literature addressing standardization of care across a clinical episode of MS-DRG 469/470 and gainsharing model. Of significant note, Froemke et al's[33] bundled payment project showed positive outcomes across the entire spectrum of care. From the outset of the project, variations were identified in cost, clinical guidelines, and interaction with the patients towards a standardized clinical process as a prerequisite to their bundled payment initiative. Preplanning took place to the level set on the outcomes of having a standardized clinical process. These outcomes centered around length of

stay (LOS), what happens after discharge, and the complete number of permitted claims targeted for improvement or reduction. The findings of this project were that no statistical evidence was found to show that improvements were related to anything other than the new standardized clinical process. Other expected outcomes were that the majority of episodes would fall under the agreed cost, generating a surplus that would be shared amongst the doctors based on the gainshare model and the meeting of target quality thresholds. There were no mortalities during the project, and there were five readmissions out of the 351 patients.[33]

While the assumption is that episode-based payments are favorable to patients, providers, and payers, there remains a gap in literature showing tangible results of bundled payment programs. Further evidence does suggest that BPCI DRG 469/470 effectively lowers cost without impacting patient care. Regarding readmissions, Froemke et al[33] made mention of another study where the mean cost of an episode minus readmissions came in at $17 543 compared to the mean cost of $31 755 for an episode that had readmissions—a net difference of $14 301, where this project realized a mean cost of $21 790. They also suggested that emphasis and attention be placed on predicting reimbursements and patient outcomes.[33]

In a different study, Iorio,[34] a member of the New York University Langone Medical Center (NYULMC) Orthopedic Surgery department, discussed the results of the department's participation in BPCI for THA and TKA for MS-469 and 470.[34] As previously discussed, THA and TKA are costly due to the variation per episode across the pre-, intra-, and postoperative care pathway. Froemke et al's[33] creation of a standardized clinical pathway was a prerequisite and one of the criteria to gauge success.[33] Iorio[34] also made mention of the success Healy et al[35] experienced when

implementing a standardized clinical pathway, attributing it to reduction in LOS and cost while maintaining the same levels of outcome and patient satisfaction. The objective of NYULMC enrolling into the BPCI program was to reduce cost and enhance patient care for TJA. Preliminary results showed a reduction in LOS, no fluctuation in readmission rates, and cost reduction without jeopardizing quality. Again, clinical pathway standardization along with rethinking the coordination of care were attributed to these results.[34]

Anoushiravani et al[36] estimated that by 2020 the number of TJAs will surpass 2 million annual procedures, including over 1.5 million total knee arthroplasties (TKAs) and more than 500 000 total hip arthroplasties (THAs). Medicare paid out more than $7 billion for more than 400 000 TJAs, or approximately $16 500 to $33 000 per procedure.[36] As noted previously, Anoushiravani et al[36] documented variation in cost and quality across TJAs. Relative to this study, theirs reviewed BPCI and their impact on degenerative joint disease (DJD) care. As an alternative payment model (APM), BPCI shifts the payment paradigm from FFS to a value-based program (VBP) mandating that cost and quality meet rigorous cost and quality thresholds. Figure 3 illustrates major health care legislation and bundle payment initiatives implemented since 2010.[36]

Enrollment in BPCI is voluntary with a three-year commit. BPCI has moved the financial strain from the patient to the provider through providing high quality, standardized orthopedic surgery for DRG 469 and 470 at an affordable cost. Further supporting what had already been stated, THAs are the third most expensive procedure Medicare patients can undergo.[36] The BPCI program is administrated as either retrospective or prospective across four payment models. In Table 2 (reproduced from Anoushiravani et al[36]), Models 1 through 3 are retrospective and

use the FFS method of payment, whereas Model 4 uses a prospective payment model in which Medicare sends a single payment covering the cost for the entire episode, which is then distributed amongst the care providers.[36]

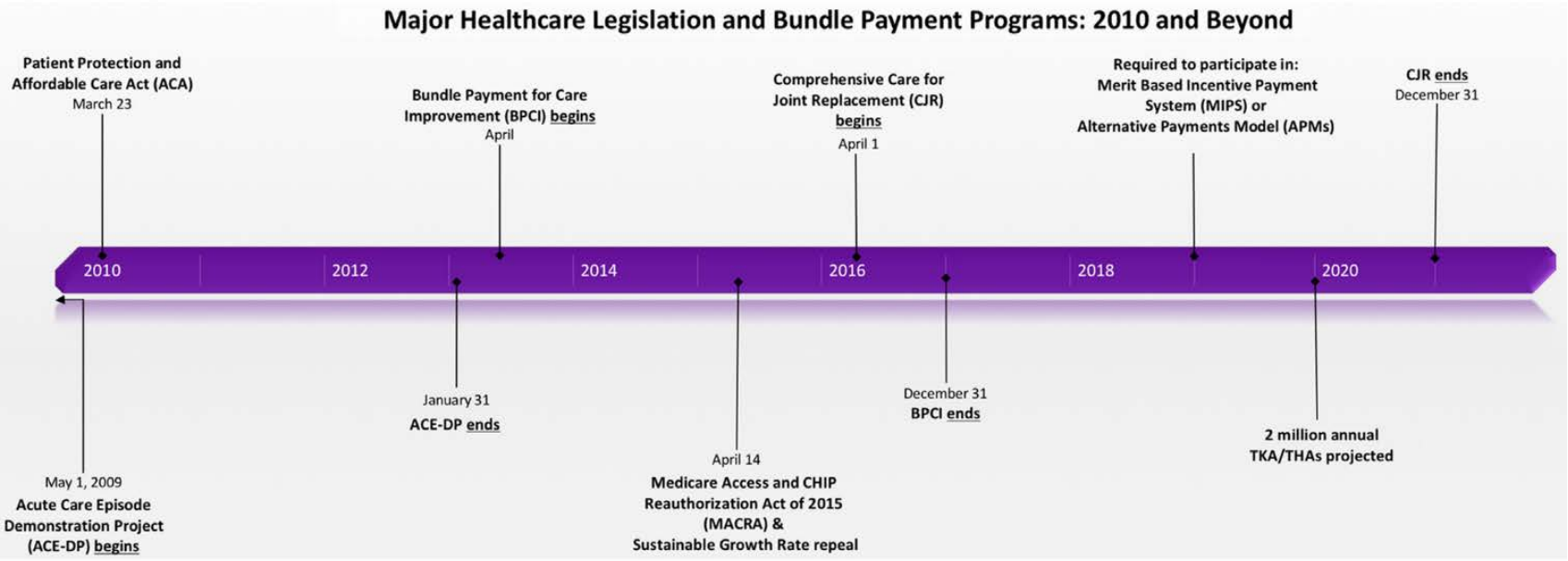



**Figure 3.** Major Health Care Legislation and Bundle Payment Programs

**Table 2.** BPCI Reimbursement Models

| Model Characteristics | Retrospective Approach | | | Prospective Approach |
|---|---|---|---|---|
| Models | Model 1 inpatient only | Model 2 inpatient + post-acute care | Model 3 post-acute care only | Model 4 inpatient only |
| Participants (as of April 1, 2016) | 1 | 649 | 862 | 10 |
| Eligible Providers | Acute care hospitals paid under IPPS<br>Health Systems<br>Physician groups<br>Physician–hospital organizations<br>Conveners of participating health care providers | Acute care hospitals paid under IPPS<br>Health Systems<br>Physician groups<br>Physician–hospital organizations<br>Post-acute providers<br>Conveners of participating health care providers | Acute care hospitals paid under IPPS<br>Health Systems<br>Physician groups<br>Physician–hospital organizations<br>Long-term care hospitals<br>Inpatient rehabilitation facilities<br>Skilled nursing facilities<br>Home health agency<br>Conveners of participating health care providers | Acute care hospitals paid under IPPS<br>Health Systems<br>Physician groups<br>Physician–hospital organizations<br>Conveners of participating health care providers |
| Clinical conditions targeted | All MS-DRGs | Eligible providers select up to 48 MS-DRGs | Eligible providers select up to 48 MS-DRGs | Eligible providers select up to 48 MS-DRGs |

**Table 2.** Continued

| Model Characteristics | Retrospective Approach | | | Prospective Approach |
|---|---|---|---|---|
| Expected discount | To be proposed by applicant<br>CMS requirements: 0% for first 6 months increases to 2% by year 3 | To be proposed by applicant<br>CMS requirements: minimum discount of 3% for episodes 30-89 days post-discharge and 2% for episodes ≥ 90 days following discharge | To be proposed by applicant | To be proposed by applicant<br>Minimum discount of 3% |
| CMS payment schedule | Hospitals: IPPS with applied Medicare discount rate<br>Physicians: traditional FFS | Traditional FFS for all providers and suppliers<br>Subject to reconciliation payments with predetermined target payments | Traditional FFS for all providers and suppliers<br>Subject to reconciliation payments with predetermined target payments | A single prospectively determined payment is made to the eligible provider<br>All providers and expenses are compensated through the bundle payment<br>Physicians forego traditional FFS payments |

Bolz and Iorio[37,38] examined potential cost savings from the implementation of BPCI. At the time, preliminary results for the first year of the BPCI program were not available for Models 1 & 4; however, Model 2 recorded 740 BPCI episodes, with the average Medicare payment for DRG 469 and 470—including postacute care (PAC)—being $32 369 for the BPCI cohort and $32 948 for the control, resulting in a statistically significant savings of $579.[37,38] Episodes excluding PAC netted $16 910 for BPCI episodes and $17 600 for the control, resulting in a savings of $690, but this was not statistically significant.[37] There was no notable change in mortality rates, but elevated results were logged for LOS and 30-day unplanned readmissions with the caveat that they later declined with the control group. For Model 3, the average Medicare payment for DRG 469 and 470 including PAC was $12 977, with the control group coming in at $13 434 for inpatient stay.[38] Also, while cost savings were realized, no meaningful results were recorded for mortality and 30-day unplanned readmission rate.[38]

The FFS payment method is the gold standard used by Medicare to pay for services. Its Achilles heel is that it does not incentivize quality, but instead rewards high usage of resources without regard to quality by paying for repeat services. BPCI's aim is to foster a spirit of cooperation between the providers in order to raise quality while reducing cost, which is contrary to what FFS delivers. A study by Clair et al[39] aimed to capture readmission costs for BPCI THA or TKA. Their study consisted of 664 Medicare beneficiaries that received either a THA or TKA and were enrolled in the BPCI program. The study recorded 80 readmissions of which 69 happened during the postoperative 90-day window. Of the 80, fifty-three readmissions occurred after THA. The cumulative readmission rate after THA was 13%. Twenty-seven readmissions were identified after TKA, with the overall

readmission rate after TKA being 8%. It was further reported that the mean reimbursement amount for THA from Medicare to the initiating facility was $20 517[39]; the mean direct cost was $31 880 to the initiating facility for these readmissions.[37] Furthermore, the mean reimbursement amount for TKA from Medicare to the initiating facility for readmissions was $20 505, and the mean direct cost to the initiating facility for these readmissions was $45 901.[39]

Clair et al[39] further reported that there was a gap in literature addressing cost for postoperative readmissions due in part to facilities only reporting on their own readmissions.[39] BPCI for DRG 469 and 470 are some of the costliest procedures reimbursed by Medicare under this program. Getting a handle on readmissions could improve the potential financial burden for the facility. Unique to this study is its use of CMS data, as earlier studies tended to contain proprietary data from the participating facility.

BPCI's value proposition is to eliminate waste and variation while improving cost and quality. To that end, Dummit et al[7] sought to evaluate the services rendered during episodes for major joint replacement or reattachment of lower extremity across pre-, intra-, and postoperative care MS-DRG 469 or 470 from October 1, 2013, to June 30, 2015. The quality outcomes of interest were unplanned readmissions, mortality, and emergency department visits. During the study, comparisons were made between those participating and those not participating in the BPCI program for major joint replacement or reattachment of lower extremity. The nonparticipating group had 29 411 episodes in the baseline year and 31 700 episodes over a 21-month intervention period, while the participating group consisted of 29 440 episodes in the baseline period across 768 hospitals and 31 696 episodes in the intervention period across 841 hospitals. Of note, there were no

meaningful or measurable difference in discharges between the nonparticipating group and those participating in the BPCI program. For those participating in the BPCI program, the mean Medicare reimbursement for hospitalization and 90-day postdischarge period were $30 551 in the baseline period, declining by $3286 to $27 265 in the intervention period. The mean Medicare reimbursement for the nonparticipating group, however, was $30 057 in the baseline period, declining by $2119 to $27 938 in the intervention period. Of note was the decline in payments for the participating group, which was estimated at $1166 more than for the nonparticipating group during the baseline and intervention periods. There was no meaningful increase or reduction seen in Medicare reimbursements 30 days before or 90 days after in quality of care, unplanned readmissions, and mortality.[7]

Dummit et al[7] also expressed concern regarding the possibility of misuse of the BPCI program for financial gain through increasing procedures which will produce more reimbursements from Medicare while recording lower cost per episode. Concern was further expressed that program participants could potentially select patients whose episode cost would be less to treat.[7] The results of this study contribute proof that incentivizing payment based on maintaining or increasing quality per episode is a viable approach. Furthermore, during the 21 months of the BPCI program, Medicare reimbursements declined more for major joint replacement or reattachment of lower extremity episodes in the participating group than in the nonparticipating group without compromising or recording a meaningful change in quality outcomes.[7]

Dundon et al[40] documented their experience with the BPCI program at NYULMC for MS-DRG 469 and 470 where LOS, readmissions, placement after discharge, and episode cost were examined and compared between years one and

three. There were 721 Medicare TJA patients in year one and 785 in year three. Of note with this study is that their 90-day all-cause readmission rate decreased from 13% to 8% and the average 90-day cost per episode decreased by 20%. Their supposition was that BPCI would increase value, quality metrics, and overall costs, and they were able to achieve this. Before BPCI was implemented, NYULMC was accruing a loss of $7000 per Medicare TJA beneficiary. As a result of the BPCI program, stringent preoperative procedures meant to optimize risk coupled with other cost reduction and improvements led to a considerable increase in the value of the health care delivered to TJA beneficiaries, thus positively impacting quality. The study clearly showed that APMs can reduce cost while not affecting or improving the quality of TJAs.[40]

Alfonso et al[31] scrutinized and contrasted cost savings for two providers enrolled in BPCI major joint replacement or reattachment of lower extremity Models 2 and 3. The per episode cost was decreased by 18.45% for Model 2 and 16.73% for Model 3, with all cost savings in the PAC. The results show that both Model 2 and 3 reduce cost and readmissions. There were 1905 episodes for Model 2 and 5410 episodes for Model 3 from 2009 to 2012, with 1680 episodes in Model 2 during the performance period and 3298 episodes for Model 3. Readmission rates decreased for Model 2 from 13.0% to 6.4%, while Model 3 decreased from 12.8% to 9.2%. Also, their findings did record inpatient costs rising from $14 256 to $15 663 for BPCI Model 2.[31]

Behery et al[41] looked to better understand patterns in 90-day readmissions. This is especially important as Medicare reimburses only a certain amount for an episode regardless of the number of readmissions. Understanding the patterns will help pre-, intra-, and postoperative patient management care impact readmissions.

It is thought by the researchers that readmissions have distinct timing, location, and patient health profile patterns based on whether they are medical or surgical related, as well as that readmissions associated with poorer pre-existing health status are medical related instead of surgical. The study consisted of 80 readmissions out of the 1412 BPCI TJA patients that were analyzed and were grouped as either medical or surgical with the central focus on time to readmission and location of readmission. The resulting readmission rate of 5.8% for TJA came in lower than previous studies using Medicare data.[41]

A study by Edwards et al[42] examined 1427 TJAs under Medicare's traditional payment program (FFS) from 2009 to 2012, as well as 461 episodes from October 2013 to September 2014 under the BPCI program. The episodes under BPCI saw a 14% reduction in cost per episode, an average decrease in LOS from 3.81 to 2.57 days, and a decrease in readmissions from 16% to 10%, for an overall decrease in cost of 23%.[42] Total joint arthroplasties are costly procedures for Medicare, and an increase in the number of TJAs is expected in the next 10 years. The study referenced the findings of others where greater than 80% of TJA cost is attributed to anchor stay along with PAC.[42] Significant cost savings have been realized when anchor stay is reduced and the discharge is to a patient's home rather than to a PAC facility, with the added caveat of a meaningful reduction in readmission rates. The expectation was that most cost savings would be realized during PAC and only nominal cost savings would be realized during the anchor stay. The results found a 14% reduction in cost for those episodes participating in the BPCI group, anchor stay cost increased $102 per episode, LOS decreased from 3.81 to 2.57 days, and readmissions decreased from 16% to 10%. Reference was made to a publication of TJA quality metrics where improvements in LOS and readmission rates, among

other rates, showed improvement. This study reaffirmed the notion that significant opportunities for improving outcomes and cost savings are realized by reducing LOS and discharging to home.[42]

Kee et al[43] documented their participation in the BPCI program for TJA. Total joint arthroplasties make up the largest share of Medicare reimbursements and are expected to increase over the next ten years. Optimization of pre-, intra-, and postoperative clinical pathway (CP) was a necessary step to participating in the BPCI program. This article sought to answer whether LOS, discharge disposition, and readmission would improve after installing the CP. The study examined 306 THA and 379 TKA procedures from April 2013 through April 2015. The THA readmission rate was 10.4% in the BPCI, discharge to home was 97.1%, and average LOS was 1.23 days, while the TKA readmission rate was 4.4%, discharge to home was 98.9%, and average LOS was 1.25 days. Therefore, a significant reduction in LOS, a higher readmission rate, and a lower discharge disposition to home with BPCI were recorded.[43]

Nichols et al[44] characterized the American health care system as succumbing to the considerable number of hip fracture procedures. The study projected total resource use and cost for Medicare beneficiaries of THA throughout pre-, intra-, and postoperative care. The areas of interest were LOS, days from admission to surgery, discharge destination, readmissions, mortality, and total costs over the 90-day episode of care. The study spanned four years, intaking hemiarthroplasty DRG 469 and 470 beneficiaries consisting of 19 634 and 77 744 patients respectively. Additionally, the study processed 1686 THA DRG 469 and 934 THA DRG 470 patients respectively. No recordable difference in mortality was recorded between hemiarthroplasty and THA. Ninety-day readmissions came in at 26% for all DRG

469 procedures (hemiarthroplasty and THA), and readmissions came in at 18% for hemiarthroplasty DRG 470 and 14% for THA DRG 470. It was reported that readmissions were considerably more pervasive for hemiarthroplasty. Mortality during readmissions ranged from 11.1% to 16.2%, with mortality significantly greater in the hemiarthroplasty patients than THA patients. Taking everything into account from admissions through 90 days after discharge, the mortality rate was 51.6% for hemiarthroplasty DRG 469 and 29.5% for hemiarthroplasty DRG 470. As it relates to THA DRG 469, the admissions through 90 days after discharge mortality rate was 48.1%, while for THA DRG 470, it was 24.9%. Patients that got past 90 days had a total cost of $27 201 for hemiarthroplasty DRG 469; $17 143 for DRG 470; $29 900 for THA DRG 469; and $17 408 for THA DRG 470.[44] It is worth noting that somewhere between 14% and 26% of patients were readmitted within 90 days. Lastly, a high mortality rate was captured from admission through 90 days after discharge: from 25% to 30% for DRG 470 and 48% to 52% for DRG 469.[44]

Middleton et al[24] assessed 601 994 90-day major joint replacement or reattachment of lower extremity episodes and their outcomes across "mortality, complications and readmissions" towards enhancing quality. Their study included Medicare fee-for-service (FFS). The results of their study across the outcomes relative to the research being conducted in this paper are that "mortality rates over 90 days were 0.4% (knee arthroplasty), 0.5% (elective hip arthroplasty), and 13.4% (nonelective hip arthroplasty)," and "readmission rates were 6.3% (knee arthroplasty), 7.0% (elective hip arthroplasty), and 19.2% (nonelective hip arthroplasty)."[24] In a related study, Navathe et al[45] examined the effects of length of stay, readmissions, and emergency department visits on quality for 3942 episodes.

Of note, there were no "statistically significant changes in readmissions or ER visits," and LOS decreased substantially by 67.0%.[45]

Siddiqi et al[46] speak to results from previous studies where reduction in LOS and readmissions have contributed to notable cost reductions. Also, as mentioned previously, Froemke et al[33] reported on physician-led standardized care pathways that have shown an "average 18% reduction in LOS."[46] Sullivan et al[47] provided analysis of the BPCI initiative. Their findings saw a decline in Medicare payments for lower extremity joint replacement episodes without a meaningful change in readmission rates and mortality. Finally, Yoon et al[48] reported on 76 654 major joint replacement or reattachment of lower extremity patients with readmission rates where LOS during readmission was increased.[48]

## 2.3 Quality

A review of the literature yields much in terms of studies concerning quality that are relevant to assessing the accuracy of predictors or determinants of risk on major joint replacement or reattachment of lower extremity surgical procedures. Hess et al[49] looked for a relationship between "interarticular fluoroplasty guided steroid injections and rapidly destructive osteoarthritis (RDOA) of the hip joint." RDOA is primarily seen in elderly females with higher Kellgren and Lawrence (KL) scores. Additionally, RDOA may "involve [a] complicated reconstructive procedure, longer operative times, and the need for special implants." It is not clear yet on the success of intra-articular steroids in treating RDOA; however, they are considered a cost-effective treatment. Results of Deshmukh et al[50] were cited in the article to suggest "better pain relief in those with more advanced hip osteoarthritis." On the other hand, McCabe et al[51] were noted to have found that "intraarticular steroid

injections may produce short-term pain relief and lead to a slight improvement in function; however, the quality of evidence was poor."[49] Hess et al's[49] experiment recorded 129 hip injections and then assessed their need for total hip arthroplasty; the diagnosis of RDOA of the hip was positioned as a predictor of arthroplasty. Results when correlating demographic information, injury, and health characteristics indicate a negligible relationship. It was found that "older patients, patients with more severe osteoarthritis, . . . and patients who identified themselves as white were more likely to have a diagnosis of RDOA." RDOA tends to be a "condition in elderly females with a higher KL score at presentation."[49] Hence, RDOA can be used as predictor of major joint replacement or reattachment of lower extremity for elderly white women.

Klingenstein et al[52] investigated whether discharging Medicare patients to their home after TKA results was successful. Their criteria for success centered around readmission and safety. They retrospectively looked at 2287 TKA patients from their hospital's major joint replacement or reattachment of lower extremity repository, observing the progress of 30 and 60 days after discharge as part of their investigation. Their results indicated that readmission was not affected, whether discharged one day after the procedure or 90 days after.[52]

Ge et al[53] looked at outcomes of TKA with patients at the same hospital who have had previous knee surgery to see if there were any correlation between patients. The findings of the study showed that previous total knee arthroplasty patients who had had complications from the conversion total knee arthroplasty were more likely to have complications.[53] It is important to note here that, while both major complications and comorbidities are included in DRG 469 procedures,

and the latter are considered in the Elixhauser indexes, comorbidities are not called out distinctly as a determinant of risk.

A study by Bala et al[54] looked at both the positive and negative outcomes of TKA as a solution for arthritis. Data was obtained through the Medicare database for the years 2005 to 2012, and both Charlson Comorbidity Index (CCI) and Elixhauser Comorbidity Index (ECI) were considered. It was found that patient health prior to the procedure did not mitigate the risk for complications after surgery.[54] In a related study, Cram et al[55] used Medicare admission data for TKA in predicting complications after the procedure. The following three groups were created from the Medicare data: no complications, one or more complications, and complications after discharge. Differences in complication rate were looked at for TKA at hospitals where the complication was not accounted for in the admission data, and ECI was applied concurrently to the admission data that did account for complications towards the ability to predict complications. The findings showed an elevated level of complications when the data were coded correctly.[55] Given ECI is a predictor of risk being used, these studies provide evidence to this approach being successful as a means to predict risk.

In the interest of further understanding the Medicare patient's capability after being discharged from surgery to an inpatient rehab hospital, Kumar et al[56] conducted a study to examine the functional capability of patients who had major joint replacement or reattachment of lower extremity. The data was assessed using Charlson Comorbidity Index, Tier Comorbidity Index, Functional Comorbidity Index, Hierarchical Condition Category (HCC), and Elixhauser Comorbidity Index. They found that the ECI and HCC performed slightly better in predicting patients' capability after discharge than the other three indexes. My current study will

likewise use the ECI, specifically its readmission and mortality index scores, to predict risk.[56] In a subsequent study, Kumar et al[57] focused on the readmission outcomes of major joint replacement or reattachment of lower extremity of Medicare patients. The comorbidity indexes used were CCI, ECI, CMS risk adjustment model, and HCC. None of the comorbidity indexes accurately predicted the patients' outcomes.[57] These results lend credence to the previous Kumar et al[56] study.

Marya et al[58] sought correlation between complication experienced by the patient and comorbidities for those undergoing TKA. Comorbidity was examined through two lenses: CCI and Age-Adjusted Charlson Comorbidity Index (ACCI). It was found that that both indexes were strong predictors of complications after surgery. ACCI proved to be the stronger predictor and showed that the highest risk of complications after surgery was from comorbidities that were organ related.[58] Pertinent to my research is the use of indexes to predict outcome as a function of comorbidity. Mehta et al[59] used several comorbidity indexes (CCI, Combined Comorbidity Score [CCS], HCC, and ECI) with their analysis of Medicare data. Their objective was to determine which indexes yielded the best outcome for patients undergoing many different types of surgery to include major joint replacement or reattachment of lower extremity. It was found that HCC accurately and reliably was the best predictor for mortality and patient outcome. The value of Mehta et al's[59] research in the context of this paper is that ECI finished a strong second, lending credibility to its vitality in predicting outcome.

Ondeck et al[60] put to test ECI for THA in an effort to determine ECI's predictive capability. The source of data was the National Inpatient Sample (NIS). Other indexes used were CCI and the Modified Frailty Index (MFI). The conclusion was ECI was a stronger determinant than CCI or MFI in predicting patient

outcomes.[60] In another study, Ondeck et al[61] compared three comorbidity indexes—CCI, ECI, and MFI—towards assessing their capability as predictor of outcome after THA. Data was sourced from the NIS. Their findings credit ECI with performing reliably and accurately when predicting patient outcome.[61]

The literature has much to say on many predictors used in my research regarding quality of outcome and reducing surgical risk in the clinical pathway. Several general studies on MJR are worthy of note. Meding et al[62] examined clinical and radiographic outcomes among patients who received each of the four major joint replacement or reattachment of lower extremity procedures. There was no significant measurable difference in pain, function, stair, and walking scores between the matched groups.[62] On another note, Gauthier-Kwan et al[63] reviewed patient capability postsurgery for outpatient TKA. All patients used the same physician for the procedure and kept a diary with functional capability and chronological data. It was found for the initial 90 days that readmissions, complications, and emergency department visits were no different for inpatient or outpatient arthroplasty.[63] Therefore, these results show the viability of outpatient total knee arthroplasty as a means to lower cost and increase access for Medicare patients while maintaining a high level of quality.[63] Li et al[64] investigated Medicare costs for TKA. Findings show varied costs across geographic location, teaching status, and education history of the physician. TKA median cost was $13 464 and $17 331, with outlier payments averaging $8000. Also, in a related study, DeJesus et al[65] reviewed a new (at the time) patient decision aid in assessing the need for TKA. While the study only looked at fifty patients, the results showed that 35 participants found the aid helpful.[65]

Several studies in the literature examine the relationship of cost and length of stay (LOS) for TKA in terms relevant to quality outcomes.[66-69] Both LOS and cost are significant predictors in my study. El Bitar et al[66] sought to determine the cause of LOS for major joint replacement or reattachment of lower extremity, given that recent evidence shows LOS has been increasing. Discharge data was sourced from the Nationwide Inpatient Sample. Two groups were formed: 3-day stay or less and 4-day stay or greater. Data analysis using chi-square showed that low-income Hispanic Medicare patients admitted on the weekend had the longest LOS for arthroplasty in rural nonteaching hospitals. The patients tended to have complications and were often discharged to an acute institution. Relative to the current study, length of stay with complications and comorbidity is used as a predictor of risk in my research.[66] Etter et al[67] sought to understand the relationship between cost, discharge status, LOS, and operating room time comparatively in two types of TKA. The findings showed that the procedure that reduced knee radius had a lower LOS, reduced costs, lower operating room time, and less discharges to SNFs than single radius knee arthroplasty. Masaracchio et al[68] examined whether timing of rehabilitation right after major joint replacement or reattachment for lower extremity affected LOS and cost, and found that earlier rehabilitation shortens LOS and reduces cost.[68] Furthermore, Williams et al[69] investigated the correlation between 90-day readmission and length of hospital stay in TKA patients using Medicare bundled payment plan. Results indicated that patients with an LOS of four or more days had an higher risk of admittance than those with an LOS of three days or less.[69]

The literature contains several studies related to the effect of a range of predictive factors on quality for post-op rehabilitation.[70-76] Graham et al[70]

investigated the outcome of patients in inpatient rehabilitation for major joint replacement or reattachment of lower extremity. Their aim was to correlate between rehabilitation facilities volume, functional status at discharge, and the setting of the discharge. The findings confirmed that major joint replacement or reattachment of lower extremity joint success is not predicated on the size of the rehabilitation facility.[70] Additionally, Keshwani et al[71] investigated whether discharge location is a strong factor in predicting outcome after TJA for lower extremity. It was shown that discharge to home rather than to an SNF or inpatient rehabilitation hospital provides the best outcome for a patient.[71] On a related note, Welsh et al[72] investigated Medicare FFS patients to determine whether postacute settings affected the readmission rates of TKA. They found that patients discharged to a community had a lower rate of unplanned readmissions than those discharged to a skilled nursing facility or inpatient rehabilitation hospital.[72]

Ottenbacher et al[73] studied 30-day readmission rates, among other complications, of Medicare major joint replacement or reattachment of lower extremity FFS patients. The findings showed that readmission rates varied based on the intake reason for rehabilitation, and that, regardless of the reason for the surgery, patients with high motor control and cognitive capability saw readmission decrease.[73] Padegimas et al[74] studied TKA patients at orthopedic hospitals to assess whether their short-term outcomes are better than general hospitals. It was found that orthopedic hospital stays were shorter and had better outcomes than other types of hospitals.[74] Additionally, Padgett et al[75] studied functional outcome from inpatient rehabilitation facilities that had TKA, and found that patients discharged from inpatient rehabilitation facilities had worse functional capability and elevated complication rates.[75]

Finally, Ramos et al[76] examined the disposition of patients discharged after TJA effects on readmission rates 30 days or less after the procedure. Previous research literature had shown a degraded patient functional outcome upon discharge to an inpatient rehabilitation hospital. Expanding on these previous studies, theirs found improved outcomes and lower readmission rates for those who were discharged home with a care attendant compared to those discharged to an inpatient rehabilitation hospital.[76]

Several studies examined age, previous TKA, and Knee Society Score as predictors of outcome.[77-80] Riddle[77] investigated the prevalence of pain-free or and symptom-free outcomes no more than two years after TKA. They found that they also were able to predict these outcomes: the lower the score on the index being used and the older the patient, the higher the likelihood of being free of pain and without symptoms two years after the procedure.[77] Furthermore, Riddle and Golladay[78] investigated risk factors for major joint replacement for lower extremity joint, particularly with hip or knee arthroplasty associated with falls two years or less after the procedure. It was found that THA patients were susceptible to falls more than TKA patients, and that patients who had previously fallen prior to surgery or who exhibited depression were at higher risk for a fall than others.[78]

Rosenthal et al[79] compared Medicare, Medicaid, and private insurance data in terms of Knee Society Scores and found Medicaid to have the lowest Knee Society Score, followed by Medicare and private insurance. This study verifies Knee Society Score's usefulness as a predictor of outcome.[79] Additionally, Kremers et al[80] reviewed patient self-reporting of TKA with the intention of removing risk through the application of risk identification and Knee Society Score measures. The collection of data involved the administration of a pre-op or post-op questionnaire to

patients having undergone TKA. The results indicated patient knee pain one to two years prior to their TKA to be a strong predictor of TKA.[80] This study shows that pain as a predictor of risk in an inpatient TKA is a strong indicator for the need to have the surgery. An understanding of this can help to reduce risk in both pre-op and intra-op.

Research also supports the use of obesity and weight loss—two components of ECI, which is used in my research—as predictors of outcome. Sayeed et al[81] investigated patient's weight as a cause of outcome and cost associated with TJA sourced from the Nationwide Inpatient Sample data. The study found that, ironically, underweight patients had a higher cost, longer stays, and more risk of anemia and deep vein thrombosis (DVT) after surgery than those morbidly obese.[81]

Many studies also attest to other comorbidities and a wide range of complications as valuable predictors of outcome for the purposes of reducing risk.[82-91] Shahi et al[82] proceeded to review hospital mortality rates of patients with periprosthetic joint infections. Findings showed that THA patients with periprosthetic joint infections had twice the risk of mortality in the hospital on a per admission basis than admittance for aseptic revisions, and that mortality rates did correlate to age, gender, the size of the hospital, rate of blood loss, and insurance status, among other factors.[82] Sorensen et al[83] studied mortality and implant survival rates among patients who underwent arthroplasty for metastatic joint disease. Their results indicated that, while mortality rates decreased, the survival rates showed no difference. Furthermore, complications were seen for some patients.[83] Additionally, Glassou et al[84] conducted research in Denmark to understand the correlation between declining mortality rates for major joint replacement or reattachment of lower extremity and comorbidities. Their results

recorded a decreased mortality rate while comorbidity increased for both intra-op and post-op.[84]

In terms of complications as predictor, such as various infections, Yi et al[85] investigated how periprosthetic joint inflection interacts with THA and TKA from a Medicare reimbursement perspective. Their analysis used Medicare claims data to uncover a $50 000 difference on average in Medicare reimbursements for patients with periprosthetic joint infections. It was also found that half of the Medicare reimbursement costs were for patient follow-up care, which is consistent with previous studies.[85] Zajonz et al[86] investigated patients with lower extremity periprosthetic joint infections and modular endoprostheses and found that patients with modular endoprostheses are 18% more susceptible to infection than those with primary endoprostheses.[86]

Botero et al[87] reviewed the incidence of venous thromboembolism (VTE) complication after major joint replacement or reattachment of lower extremity for patients who also had hemophilia A or B. The objective of the study was to account for VTE prevalence in these patients and formulate reduction strategies for the complications. It was determined that VTE was prevalent in the study and that it could be reduced through pharmacology or a compression device. They concluded that considering complications as a predictor of risk after surgery can alleviate a prolonged length of stay or readmission.[87]

Additionally, Son et al[88] investigated if open debridement and polyethylene exchange affected patients with infections after TKA. They determined that antibiotic therapy is only useful if it is begun within a five-day period at the start of infection. Antibiotic therapy also will not work if the patient has rheumatoid arthritis.[88] Manian and Kelly[89] conducted a retrospective study to examine if there

was any correlation with post-surgery bacterial skin and soft tissue infections and TKA affecting the same limb. They found that TKA patients are highly susceptible to acute bacterial skin and soft tissue infections.[89] Also, Poole and Brandenstein[90] investigated the effects of a type of neurological disease on lower extremity mobility in their daily activities. The findings confirmed their suspicions that MJR is present with post-surgery bacterial skin and soft tissue infections.[90]

Regarding the literature on comorbidities as predictor, Tannenbaum et al[91] examined patient safety indicators for TKA, where private insurance patients had a lower patient safety indicator than Medicare, Medicaid, or self-paid patients. The data was sourced from the Nationwide Inpatient Sample. When examining the data and comorbidities, the results were indifferent to patient safety indicators for patients who were privately insured, on Medicaid or Medicare, or self-paid.[91]

Finally, one study suggests a further factor to investigate in my research as a potential predictor of outcome. Boylan et al[92] examined the prevalence of adverse postsurgical outcomes in knee arthroplasty patients. It was determined that TKA patients' procedures on Wednesday or Friday had a longer length of stay and increased surgical cost; that procedures on Monday or Tuesday had a decreased length of stay and cost; and that cost was elevated on Thursdays.[92] It may be possible in my research to investigate day of surgery as a potential predictor of outcome by sorting the date of surgery by its corresponding day of week and running outcomes based on that.

Machine learning, a branch of artificial intelligence, is an emerging field centered on the ability of developing algorithms that enable a computer to learn by instinctively forming rules and patterns from voluminous data. It is an interdisciplinary field composed of data mining, statistics, and pattern recognition,

among others,[93] and it has quickly become a game changer and a necessary augmentation for every conceivable industry. Related to this, data mining is concerned with classifying and predicting outcomes based on machine language algorithms.[94] There is a lack of research using statistical machine learning to mine Medicare inpatient claims data for major joint replacement or reattachment of lower extremity data for patterns and predictors of risk. Furthermore, a literature gap exists for studies demonstrating other researchers using machine learning algorithms and artificial intelligence to unearth predictors of risk in the aforementioned Medicare data. Therefore, the objective of this research is to examine retrospective Medicare inpatient claims data using machine learning algorithms for determinants as strong predictors of risk in an inpatient stay for major joint replacement or reattachment of lower extremity.

# CHAPTER III
# METHODS

## 3.1 Quantitative Paradigm

This inquiry into predictors of risk is through the philosophical lens of Postpositivism, as it is deterministic in its pursuit in identifying and assessing is associated with the affect outcomes.[95] Furthermore, it takes a reductionist approach, in that a combination of predictor variables are reduced to a distinct set of concepts.[95] This set of concepts is used to test the hypothesis and research questions, then the tests are observed, measured, and compared to what is known regarding predictors of risk. Additionally, the inquiry design is experimental, as associations are investigated between known predictors of risk (e.g., emergency department visits, readmissions, and mortality), then, excluding those predictors, the outcomes of the two groups are retested and compared using data analysis and statistical procedures to examine the relationship between variables. Hence, the paradigm or method of this study is designated as quantitative.

## 3.2 Research Design

This research has been designed from a retrospective perspective, with the intention to hypothesize whether certain variables in the inpatient claim data had an association to a novel risk variable that was created for each claim. This design was chosen with the understanding that variables in the data could be confounding to the novel risk flag that was created for each claim. The confounding variables

that were associated with emergency department visit, readmission, and mortality were removed as predictors in the machine learning model creation, with the intention of removing any bias that could have been introduced. Additionally, the design of the experiment is binary classification using supervised machine learning. The algorithm selection took the path illustrated in Figure 4, beginning at START, continuing along the decision path through a series of questions (e.g., (1) sample > 50; (2) predicting a category; (3) do you have labeled data; and (4) sample < than 100K), then proceeding into the classification section of the diagram.[96]

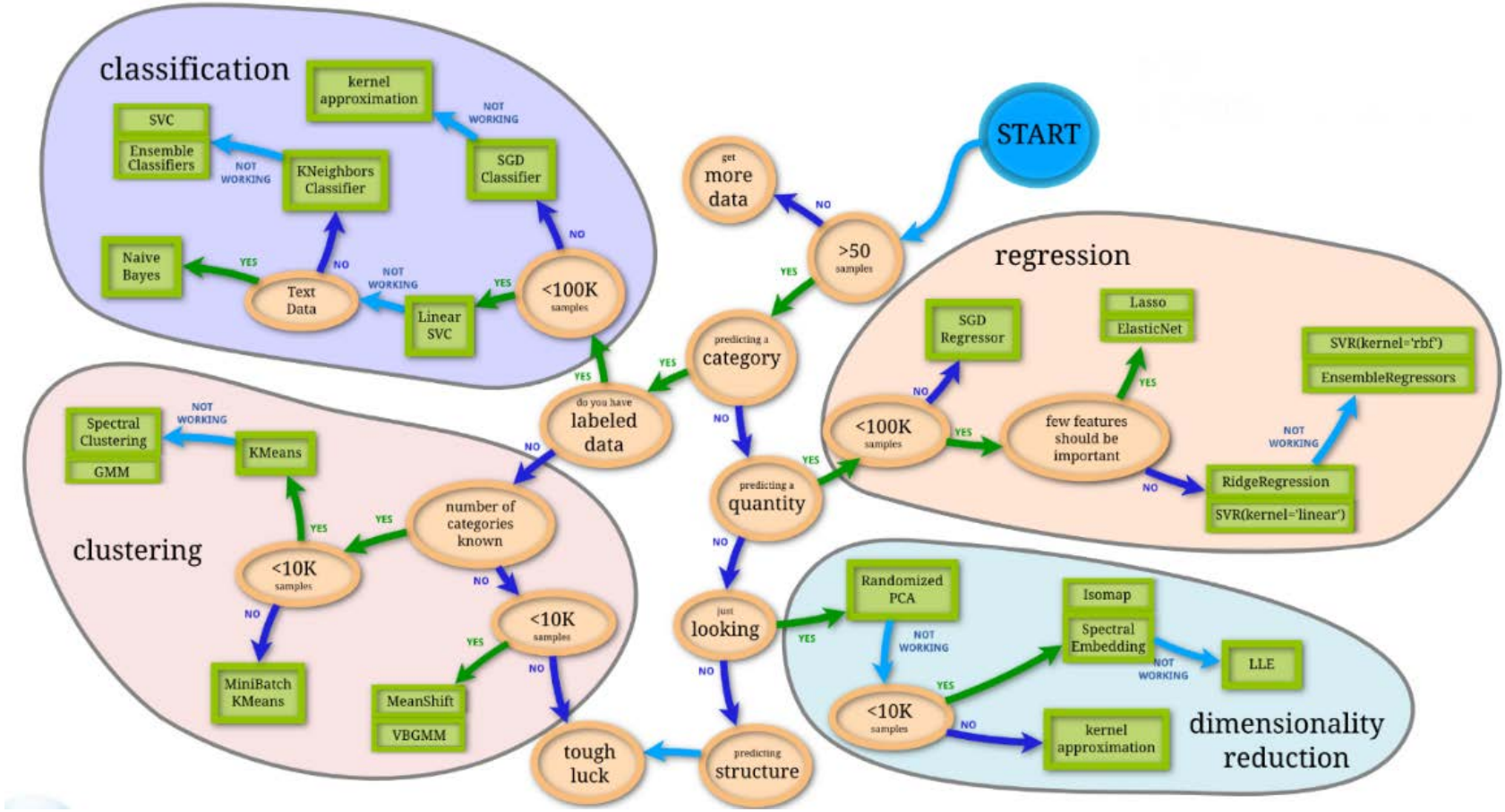



**Figure 4.** Machine Learning Algorithm Selection Path (Scikit-Learn Algorithm Cheat-Sheet)

Medicare Limited Data Sets of Inpatient Claim records were procured from Medicare via a research application. Four years were selected (2013-2016) with the option of purchasing of either the entire file for each year or five percent of the records for each year. The records are randomly extracted using an SAS random selection command by General Dynamics Information Technology, who administers the extraction of the requested data for Medicare for all beneficiary inpatient claim records. Due to cost constraints, it was decided to procure 5% of the records for each year. The combined total records for all years was approximately 2.3 million beneficiary all-cause final claim records from Medicare; 74 187 claims were extracted with major joint replacement. The sample for this study was created by extracting records only for those whose claims covered admittance through discharge at acute hospitals for surgical procedure DRG 469 or 470, given that this study is a retrospective look at the beneficiary inpatient claim record for said surgical procedures. Further data cleansing, processing, and transformation was applied using SAS. Counters were created to track emergency department visit, length of stay, and readmissions and stored in each beneficiary claim record as new variables. The sample was further grouped into acceptable risk and questionable risk based on whether there had been a readmission, emergency department visit, or death during the admission and 90 days after discharge. Tableau was used to create 2D plots and graphs of the sample to visually gain insight to possible associations between variables. An Elixhauser Comorbidity Index (ECI) score for readmission and mortality was calculated for each beneficiary claim record and stored as a new variable in each claim. The ECI scores were calculated using 25 International Classification Diagnosis (ICD) codes contained in each beneficiary claim record using SAS code obtained from H-CUP. The ICD codes contained in

each beneficiary claim record were either ICD-9 or ICD-10. For each beneficiary claim record, ICD codes were transformed from ICD-9 to ICD-10 using developed SAS code created to crosswalk the ICD-9 codes to ICD-10. Through this process, all ICD-9 codes were overwritten in the sample as ICD-10 codes. Two other risk flags were created and stored as new variables in each beneficiary claim record: Elixhauser Readmission and Mortality risks. These risk flags were calculated by taking the lower and upper limits for the ECI scores and (a) setting the flag to 1 if the beneficiary claim record was greater than the mean ECI score for readmission and mortality, or (2) setting the flag to 0 if it was less than the mean ECI score for readmission and mortality. Then, the novel risk field was coded as either 0 for questionable acceptable risk or 1 for acceptable risk based on the criteria in Table 3 and stored in each beneficiary claim record as a new variable. Finally, all variables used in the calculation of the novel risk flag and associated with emergency department visits, readmissions, and mortality were removed from the sample.

After the sample was first imputed in SAS Enterprise Miner (EM), it was exported to three data mining platforms—MATLAB, EM, and MLjar (see below for additional details)—then transformed into the appropriate file format using STAT/Transfer or Microsoft Excel. The algorithms selected did not duplicate or overlap another data mining software's algorithms, thereby forming a distinct and diverse suite of models.

- The MATLAB sample was divided into a Train and Test dataset. The Train and Test datasets, comprising 80% and 20%, or 59 350 and 14 837, respectively, were created by random selection using the RAND command in MATLAB source code.

- The EM sample was divided into a Train and Test dataset using the Data Partition node in EM. The Train and Test datasets, comprising 80% and 20%, or 59 350 and 14 837, respectively, were created by random selection in the data partition node using a random seed of 12345.
- The MLjar samples for the Train and Test datasets were exported from the output of the data partition node in EM. The Train and Test datasets, comprising 80% and 20%, or 59 350 and 14 837, respectively, were created by random selection in the data partition node using a random seed of 12345.

There are 74 187 beneficiary claim records in the study, consisting of 3721 DRG 469 beneficiary claim records and 70 466 DRG 470 beneficiary claim records. It is well documented by previous studies that emergency department visits, readmissions, and mortality are key indicators of risk. This study flagged each claim record as acceptable risk or questionable risk based on the criteria listed in Table 3. Thereafter, the study looked to see if a classification algorithm could accurately predict the risk flagged for each beneficiary claim record and determine which predictors where the most important in predicting the flag.

**Table 3.** Risk Flagging per Claim Record

| Risk Flag | Condition |
|---|---|
| Acceptable Risk | If Emergency Department Visit = 0<br>If 90-day Readmissions = 0<br>If Patient Status = 1 (Discharged) |
| Questionable Risk | If Emergency Department Visit = 1 or greater<br>If 90-day Readmissions = 1 or greater<br>If Patient Status = 2 (Died) |

## 3.3 Unified Data Mining Theory

The theory used in this study is the Unified Data Mining Theory (UDMT) formulated by Khan et al,[97] which is used to combine the processes of clustering, classification, and visualization into a unified theory. While UDMT is a rather new theoretical framework and has not seen widespread adoption, having been first penned in 2016, it holds true to the steps used in this study and has seen limited acceptance. Theory development in data mining is in its infancy. The underlying theoretical foundation is that without clustering, classification is not possible; without classification, there is nothing to visualize; and without visualization, knowledge does not exist. This research adapted the UDMT model to describe the design under test. We first passed the partitions of the dataset through an outcome novel algorithm, then through a set of classification and visual algorithms. Next, the obtained results were interpreted and evaluated to extract the knowledge. Thereafter, the algorithm with the highest ROC was the measure used to select the model. Thus, data mining processes are unified through the composition of functions as described in the model illustrated in Figure 5.

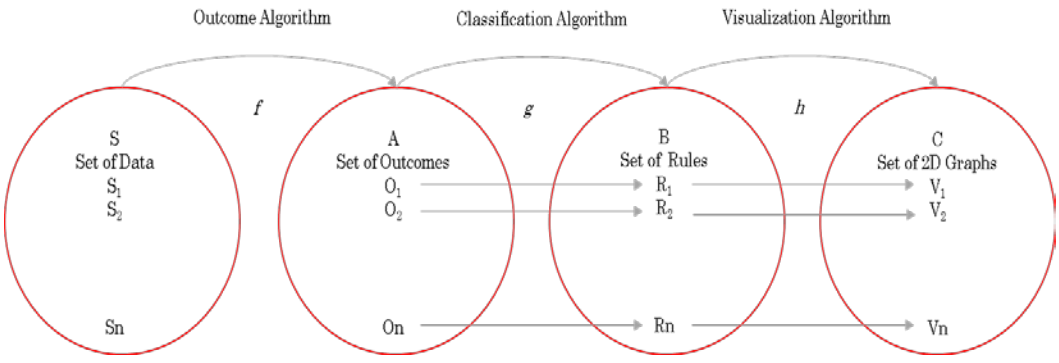



**Figure 5.** Unified Data Model Theory Integrated

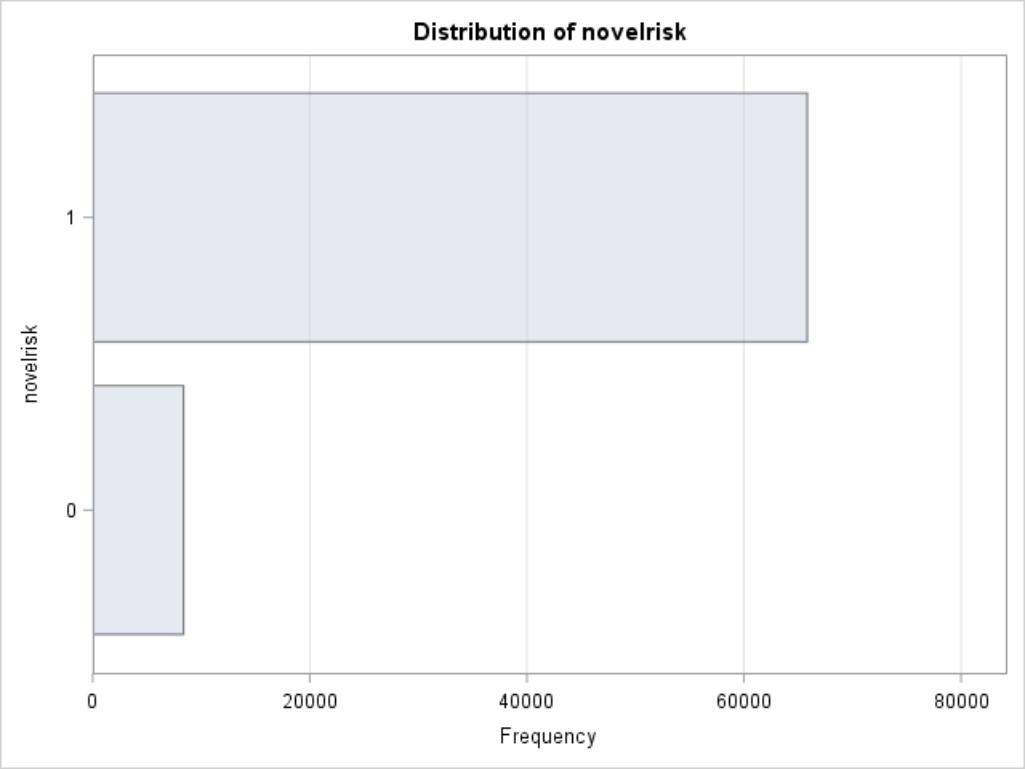
### 3.4 Beneficiaries, Datasets & Sampling

The Inpatient Limited Data Sets (LDS) from the Center for Medicare and Medicaid Services (CMS) were used to capture the claims data from hospitals which contain, among other things, the diagnosis, dates of treatment, amount reimbursed, and beneficiary data. The LDS also came with the revenue files for each year, which contained the revenue codes that describe the various charges. Due to the prohibitive cost of procuring 100% of the LDS records for each year, the study used 5% of the Inpatient LDS for years 2013-2016, as described in Table 4.

**Table 4.** Inpatient LDS DRG 469 & 470 by Year

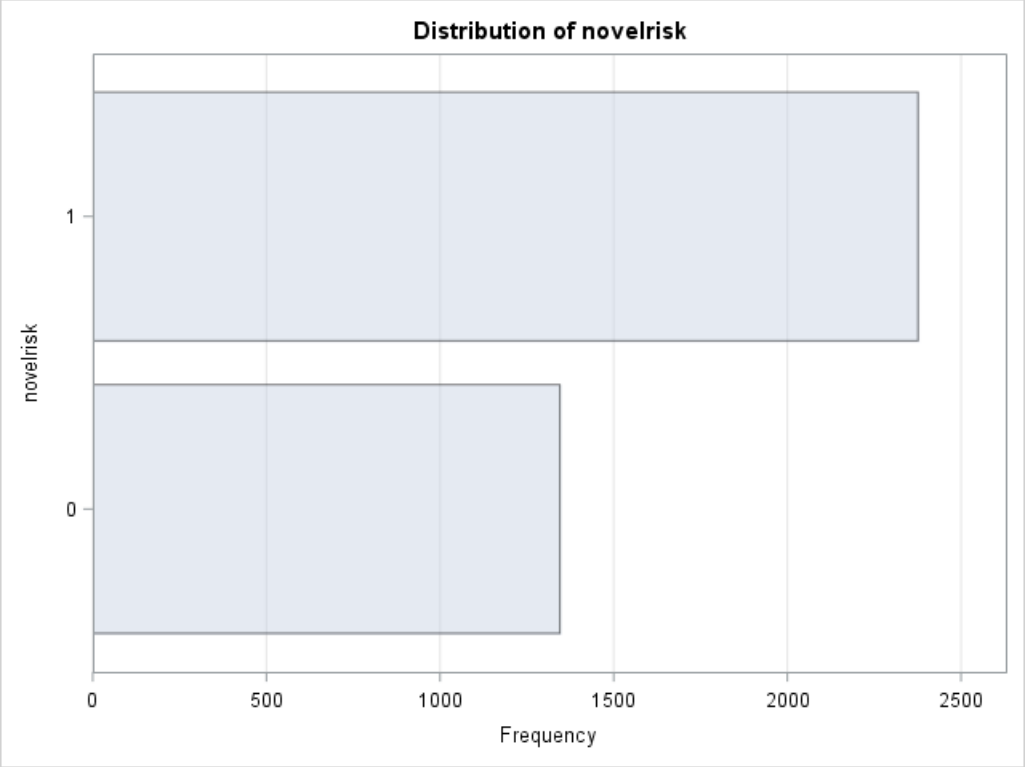
| Year | DRG 469 & 470 | % | Total Records | % |
|---|---|---|---|---|
| 2013 | 12 064 | 2.07 | 582 422 | 25.56 |
| 2014 | 21 209 | 3.75 | 564 875 | 24.79 |
| 2015 | 21 167 | 3.73 | 567 163 | 24.89 |
| 2016 | 19 747 | 3.50 | 564 177 | 24.76 |
| Total | 74 187 | 3.26 | 2 278 637 | 100.00 |

Of the 74 187 beneficiary claims listed in Table 4, 67 986 are distinct beneficiaries. The subsequent 6201 beneficiary claims thus belong to individuals within the set of distinct 67 986 beneficiaries (i.e., distinct beneficiaries can have one or more additional claims). It is important to note, though, that, while a beneficiary may have multiple claims, each beneficiary claim is an unique observation in and of itself. The following figures represent the breakdown of the types of risk associated with the claims. Figure 6 shows the percentage of claims that have questionable or acceptable risk. Figure 7 and Figure 8 show percentage of claims that have questionable or acceptable risk by DRG.




| novelrisk | Frequency | Percent |
|---|---|---|
| Questionable Risk 0 | 8357 | 11.26 |
| Acceptable Risk 1 | 65 830 | 88.74 |

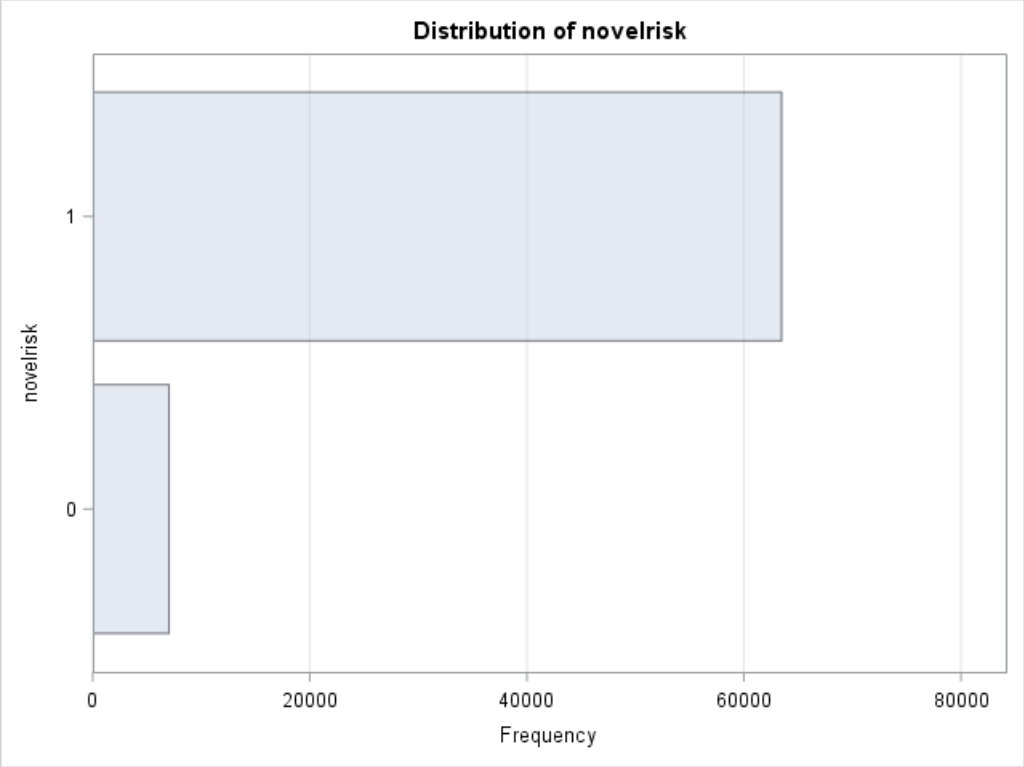
**Figure 6.** Percentage of Beneficiary Claims with Questionable and Acceptable Risk.




DRG=469

| novelrisk | Frequency | Percent |
|---|---|---|
| Questionable Risk 0 | 1345 | 36.15 |
| Acceptable Risk 1 | 2376 | 63.85 |

**Figure 7.** Percentage of DRG 469 claims that have questionable or acceptable risk.




DRG=470

| novelrisk | Frequency | Percent |
|---|---|---|
| Questionable Risk 0 | 7012 | 9.95 |
| Acceptable Risk 1 | 63 454 | 90.05 |

**Figure 8.** Percentage of DRG 470 claims that have questionable or acceptable risk.

## 3.5 Tools

- ✓ SAS Studio 3.7 from SAS Institute
- ✓ SAS Enterprise Guide (EG) 14.2 from SAS Institute
- ✓ Tableau 10.5 from Tableau Software
- ✓ Elixhauser Comorbidity Software, Version 3.7, H-CUP
- ✓ SAS Enterprise Miner(EM) 14.2 from SAS Institute
- ✓ Stat/TransferStat14 from Circle Systems
- ✓ Microsoft Excel
- ✓ MATLAB R2016b from MathWorks
- ✓ MLJAR from MLJAR

## 3.6 Data Analysis Procedures

Listed in Table 5 are the procedural steps used to setup the sample, create summary statistics and inferential statistics, and conduct the exploratory data mining and supervised machine learning.

**Table 5**. Data Analysis Procedures

| | |
|---|---|
| Step 1. | The inpatient claims data was extracted, transformed, and loaded in order to create the sample dataset using SAS Studio and SAS Enterprise Guide. Emergency department visits and readmissions counters were calculated for each beneficiary claim record. The novel risk flag was created for each beneficiary claim record based on the criteria in Table 3. Two additional risk flags were created and stored in each beneficiary claim record derived from the elixhauser readmission index and elixhauser mortality index. |
| Step 2. | H-CUP elixhauser comorbidity software code was adapted to the sample dataset to identified comorbidities. |
| Step 3. | ICD-9 crosswalk to ICD-10 created and updated using SAS Studio. |
| Step 4. | Tableau was used to create visual charts enabling the researcher to observe patterns, trends, and outliers in the data. |
| Step 5. | The sample dataset was loaded into SAS Enterprise Guide where summary statistics and binary logistic regression were calculated. |

**Table 5.** Continued

| | |
|---|---|
| Step 6. | The sample dataset was converted from SAS format to a MATLAB dataset format using Stat/TransferStat14. Machine learning algorithms were used for data mining using MATLAB R2016b from MathWorks. |
| Step 7. | Training and Test datasets were created in SAS EM from the data partition node. Machine learning algorithms were used for data mining of the datasets using SAS Enterprise Miner |
| Step 8. | Training and Test datasets were created from Excel after converting them from SAS dataset format to Excel 7 format using Stat/TransferStat14. Machine learning algorithms were used for data mining of the Excel Training and Test files using MLJAR. |

### 3.6.1 Create SAS Inpatient Dataset Procedures

**Table 6**. SAS Inpatient Claims Extraction, Transformation, and Load

| | |
|---|---|
| Step 1. | Merge Inpatient LDS SAS CSV files 2013-2016. |
| Step 2. | Extract Acute Hospital beneficiary claim records. |
| Step 3. | Calculate Length of Stay. |
| Step 4. | Calculate 90-Day Readmissions. |
| Step 5. | Create Distribution Table for DRG. |
| Step 6. | Create Distribution Table for Gender. |
| Step 7. | Create Distribution Table for Race. |
| Step 8. | Create Distribution Table for Age Range. |
| Step 9. | Create Distribution Table for State. |
| Step 10. | Merge Emergency Department visits from Inpatient Revenue Tables. |
| Step 11. | Calculate emergency department visits per beneficiary claim record. |
| Step 12. | Calculate the novel risk for each inpatient claim record and add column to sample. |
| Step 13. | Generate dataset for MATLAB processing. |
| Step 14. | Convert Gender, Race, Age, State and Qualify Flags into a descriptive label for Tableau processing. |
| Step 15. | Generate dataset for Tableau processing. |

### 3.6.2 Create Elixhauser Comorbidity Index

**Table 7.** Elixhauser Comorbidity Index

| | |
|---|---|
| Step 1. | Create format and library. |
| Step 2. | Create variables. |
| Step 3. | Create index scores. |

### 3.6.3 ICD-9-CM Crosswalk to ICD-10-CM

**Table 8.** ICD-9-CM Crosswalk to ICD-10-CM

| | |
|---|---|
| Step 1. | Download ICD-9-CM to ICD-10-CM table in SAS format[98]. See Table 5. |
| Step 2. | Load SAS ICD-9 to ICD-10 table using SAS. Index the ICD-10 column. |
| Step 3. | Read through the sample dataset one record at a time. For each record, there are 25 ICD codes. Take each code and perform a lookup in the ICD-9 to ICD-10 table. If a record is found, replace the ICD-9 code with an ICD-10 code in the sample. |

### 3.6.4 Data Visualization Using Tableau

**Table 9.** Tableau Data Insight and Visualization Steps

| | |
|---|---|
| Step 1. | Load Tableau dataset created in SAS into Tableau. |
| Step 2. | Create visualization Age, Race by Average Medicare Claim Payment within Gender. |
| Step 3. | Create visualization Comorbidities by Gender. |
| Step 4. | Create visualization Comorbidities by Race. |
| Step 5. | Create visualization Comorbidities by Count. |

### 3.6.5 Statistical Tests

**Table 10.** Statistical Tests

| | |
|---|---|
| Step 1. | Load sample in SAS Enterprise Guide. |
| Step 2. | Run Summary Statistics. |
| Step 3. | Run Logistic Regression. |

### 3.6.6 Statistical Machine Learning Using MATLAB

**Table 11**. MATLAB Model Creations

| | |
|---|---|
| Step 1. | Load MATLAB dataset generated from Stat/Transfer. |
| Step 2. | Convert MATLAB dataset to MATLAB table. |
| Step 3. | Create labels for each column in table. |
| Step 4. | Convert character predictor fields to numeric. |
| Step 5. | Run script to produce random selection to create Train and Test datasets. |
| Step 6. | Run classification application learner. |
| Step 7. | Select Train dataset from workspace. |
| Step 8. | Select predictor and response features . |
| Step 9. | Set cross-validation to 15 folds. |
| Step 10. | Run all classification algorithms against the Train dataset. |
| Step 11. | Review Receiver Operating Curve (ROC) chart for each model. Select best ROC. |
| Step 12. | Export most accurate model. |
| Step 13. | Run exported model against Test dataset. Create 2D ROC plot. |

### 3.6.7 Statistical Machine Learning Using SAS EM

**Table 12.** SAS Enterprise Miner HP BN Classifier—Naïve Bayes

| | |
|---|---|
| Step 1. | Create a project. |
| Step 2. | Select data source under test: inp_claims_lds2013-2016. |
| Step 3. | Create diagram for Naïve Bayes. |
| Step 4. | Add data source inp_claims_lds2013-2016 to Naïve Bayes diagram: inp_claims_lds2013-2016. Edit variables for role, fields to drop or keep and level. |
| Step 5. | Add impute node to diagram. Change property type under indicator variable to: unique. Change property role under indicator variable to: input. Connect source node to impute node. |
| Step 6. | Add data partition node to the diagram. Change data set allocations property Training to 80 and change data set allocations property Test to 20. Connect impute node to data partition node. |

**Table 12.** Continued

| | |
|---|---|
| Step 7. | Add transform variable node to the diagram. Select the ellipsis in formulas property. Select create icon and add transformation.<br>• Name: _fold_<br>• Type: Numeric<br>• Level: Nominal<br>• Role: Segment<br>In the Formula box enter: int(ranuni(1)*15)+1 and press Build, then OK, then OK again. Connect data partition node to transform variable node. Right click transform variable node and select run. |
| Step 8. | Add filter node to the diagram. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so a grated pattern now fills the bar. Repeat procedure for bars 3 through 15. Then press apply filter. Then OK. Connect transform variable node to filter node. |
| Step 9. | Add filter node to the diagram. This filter node now is named filter 2. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1, 3 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 2 node. |
| Step 10. | Add filter node to the diagram. This filter node now is named filter 3. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-2, 4 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 3 node. |
| Step 11. | Add filter node to the diagram. This filter node now is named filter 4. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-3, 5 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 4 node. |

**Table 12.** Continued

| | |
|---|---|
| Step 12. | Add filter node to the diagram. This filter node now is named filter 5. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-4, 6 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 5 node. |
| Step 13. | Add filter node to the diagram. This filter node now is named filter 6. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-5, 7 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 6 node. |
| Step 14. | Add filter node to the diagram. This filter node now is named filter 7. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-6, 8 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 7 node. |
| Step 15. | Add filter node to the diagram. This filter node now is named filter 8. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-7, 9 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 8 node. |
| Step 16. | Add filter node to the diagram. This filter node now is named filter 9. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-8, 10 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 9 node. |

**Table 12.** Continued

| | |
|---|---|
| Step 17. | Add filter node to the diagram. This filter node now is named filter 10. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-9, 11 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 10 node. |
| Step 18. | Add filter node to the diagram. This filter node now is named filter 11. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-10, 12 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 11 node. |
| Step 19. | Add filter node to the diagram. This filter node now is named filter 12. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-11, 13 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 12 node. |
| Step 20. | Add filter node to the diagram. This filter node now is named filter 13. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-12, 14 through 15. Then press apply filter. Then OK. Connect transform variable node to filter 13 node. |
| Step 21. | Add filter node to the diagram. This filter node now is named filter 14. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1-13, 15. Then press apply filter. Then OK. Connect transform variable node to filter node 14. |

**Table 12.** Continued

| | |
|---|---|
| Step 22. | Add filter node to the diagram. This filter node now is named filter 15. Select the ellipsis in class property. Scroll down to _fold_ under name column and select row. In the window titled 'Select values to remove from the sample,' all bars are solid. Click on bar 2 so grated pattern now fills the bar. Repeat procedure for bars 1 through 14. Then press apply filter. Then OK. Connect transform variable node to filter node 15. |
| Step 23. | Add HP BN Classifier to diagram. Change Network Model property to Naïve Bayes. Change the variable selection property to: yes. Rename HP BN Classifier to Naïve Bayes. Connect filter node to Naïve Bayes. |
| Step 24. | Repeat steps 23-26 fourteen more time starting with filter 2 node through filter 15 node. |
| Step 25. | Add Model Comparison node to diagram. Change Selection Statistic property to ROC. Connect all 15 classifier nodes to Model Comparison node. Right click on Model Comparison node and select Run. |
| Step 26. | After the Model Comparison node has completed processing, right click and select Results. Best model based on ROC selection criteria will be the very first row. |

### 3.6.8 Statistical Machine Learning Using MLJAR

**Table 13.** MLJAR Model and ROC Plot Creation

| | |
|---|---|
| Step 1. | Create Training and Test datasets in the SAS EM Data Partition node. |
| Step 2. | Save and export datasets to local directory on computer. |
| Step 3. | Run STAT/Transfer to convert datasets from SAS dataset format to Excel 2007 format. |
| Step 4. | Open and save excel files as using csv format. |
| Step 5. | Go to MLJAR website and create a project. |
| Step 6. | Create new Training and Test datasets from the csv data sources. |
| Step 7. | Preview datasets and select target for each dataset. |

**Table 13.** Continued

| | |
|---|---|
| Step 8. | Add and run new experiment:<br>1. Create title of experiment.<br>2. Select validation as k-fold validation.<br>3. Select 15 folds.<br>4. Select shuffle samples and stratify classes in folds.<br>5. Select input dataset as training dataset.<br>6. Select preprocessing as 'fill with median' (fills categorical missing values with the most frequent value).<br>7. Select learning algorithms: (a) Extreme Gradient Boosting, (b) LightGBM, (c) Random Forest, (d) Regularized Greedy Forest, (e) Extra Trees.<br>8. Select tuning ROC as tuning metric.<br>9. Select tuning mode as normal (5-10 models).<br>10. Select time limit for each model as 5 minutes. |
| Step 9. | Review results and select best algorithm to run prediction with Test dataset. |
| Step 10. | Run all classification algorithms. |
| Step 11. | Review model with the most Receiver operating curve (ROC). |
| Step 12. | Export most accurate model. |
| Step 13. | Run exported model against test feature set using created scripts to produce the ROC of the Test dataset. |
| Step 14. | Create ROC 2D plot. |

# CHAPTER IV
# RESULTS

## 4.1 Statistical Exploration and Summary

The variables in this study were both continuous and categorical, thus forming a mixed model. The demographics of the claims are presented in Table 14. The sample size consisted of 74 187 inpatient claims. Of that sample, 3721 were DRG 469 and 70 466 were DRG 470. The age group 85 and older had the highest percentage of DRG 469 claims at 32.28%, whereas in DRG 470, the age groups 65 to 69 and 70 to 74 made up 52% of the claims. Both DRG 469 and 470 recorded less than 10% of the claims in the age group 64 and younger. Of note, claims for DRG 470 in age group 85 and older had the lowest percentage overall at slightly over 9 percent. Women accounted for the highest percentage across both DRG 469 and 470, 60.55% and 63.79% respectively. All 50 states and the District of Columbia were represented in the sample along with claims from Guam and Puerto Rico. While there were DRG claims from Europe, they were statistically insignificant. California had the highest occurrence of DRG 469 claims at 7.55%, whereas Florida had the highest percentage of DRG 470 claims at 6.54%. Additionally, summary statistics showing the central tendency of the predictors are presented in Table 15, classified by the novel risk variable.

**Table 14.** Beneficiary Demographics

| Parameter | DRG 469 | DRG 470 |
|---|---|---|
| Sample size (N) | 3721 | 70 466 |
| Age Group | | |
| 64 and younger | 9.27 | 9.43 |
| 65-69 | 11.53 | 28.86 |
| 70-74 | 13.60 | 23.14 |
| 75-79 | 16.07 | 18.00 |
| 80-84 | 17.25 | 11.52 |
| 85 and older | 32.28 | 9.05 |
| Female (%) | 60.55 | 63.79 |
| Male (%) | 39.45 | 36.21 |
| State Code (%) | | |
| Alabama | 2.42 | 2.22 |
| Alaska | 0.08 | 0.17 |
| American Samoa | | 0.00 |
| Arizona | 1.91 | 1.98 |
| Arkansas | 1.29 | 1.25 |
| Asia | | 0.01 |
| California | 7.55 | 6.27 |
| Canada | | 0.00 |
| Central America and West Indies | | 0.00 |
| Colorado | 1.40 | 1.64 |
| Connecticut | 1.61 | 1.50 |
| District of Columbia | 0.21 | 0.17 |
| Europe | | 0.01 |
| Florida | 6.88 | 6.54 |
| Georgia | 2.98 | 3.08 |
| Guam | 0.03 | 0.01 |
| Hawaii | 0.21 | 0.15 |
| Idaho | 0.51 | 0.72 |
| Illinois | 5.13 | 4.54 |
| Indiana | 3.01 | 2.63 |
| Iowa | 1.48 | 1.84 |
| Kansas | 1.42 | 1.47 |
| Kentucky | 2.34 | 1.50 |
| Louisiana | 0.89 | 1.18 |

**Table 14.** Continued

| Parameter | DRG 469 | DRG 470 |
|---|---|---|
| Maine | 0.54 | 0.65 |
| Maryland | 2.07 | 2.52 |
| Massachusetts | 2.07 | 2.11 |
| Mexico | 0.03 | 0.01 |
| Michigan | 3.63 | 3.50 |
| Minnesota | 2.10 | 2.39 |
| Mississippi | 1.10 | 1.24 |
| Missouri | 2.85 | 2.49 |
| Montana | 0.30 | 0.52 |
| Nebraska | 1.32 | 1.11 |
| Nevada | 0.54 | 0.67 |
| New Hampshire | 0.40 | 0.60 |
| New Jersey | 2.74 | 2.92 |
| New Mexico | 0.46 | 0.53 |
| New York | 3.76 | 3.86 |
| North Carolina | 3.68 | 3.59 |
| North Dakota | 0.48 | 0.33 |
| Ohio | 3.60 | 3.31 |
| Oklahoma | 1.40 | 1.76 |
| Oregon | 1.32 | 1.16 |
| Pennsylvania | 3.33 | 4.13 |
| Philippines | | 0.00 |
| Puerto Rico | 0.19 | 0.14 |
| Rhode Island | 0.05 | 0.27 |
| South Carolina | 2.02 | 2.29 |
| South Dakota | 0.51 | 0.55 |
| Tennessee | 3.06 | 2.27 |
| Texas | 6.50 | 6.41 |
| Utah | 0.48 | 0.82 |
| Vermont | 0.19 | 0.30 |
| Virgin Islands | 0.03 | 0.03 |
| Virginia | 3.06 | 3.14 |
| Washington | 2.26 | 2.13 |
| West Virginia | 0.67 | 0.76 |
| Wisconsin | 1.56 | 2.32 |
| Wyoming | 0.35 | 0.30 |

**Table 15.** Summary Statistics Results: The MEANS Procedure

| novelrisk | N Obs | Variable | Mean | Std Dev | Minimum | Maximum | N |
|---|---|---|---|---|---|---|---|
| 0 | 8357 | claimpayment | 13 930.41 | 5552.64 | 0 | 94 118.39 | 8357 |
| | | providerstate | 25.747 038 4 | 15.048 267 8 | 1.000 000 0 | 65.000 000 0 | 8357 |
| | | organizationphysician | 1 488 662 519 | 285 436 266 | 1 003 185 472 | 1 992 812 544 | 8357 |
| | | attendingphysician | 1 497 259 729 | 291 380 623 | 1 003 010 944 | 1 992 999 168 | 8357 |
| | | operatingphysician | 1 501 785 942 | 290 169 507 | 1 003 010 944 | 1 992 974 208 | 8357 |
| | | drg | 469.839 057 1 | 0.367 500 3 | 469.000 000 0 | 470.000 000 0 | 8357 |
| | | drgoutlierstay | 0.259 183 9 | 1.217 522 4 | 0 | 8.000 000 0 | 8357 |
| | | agegroup | 4.167 284 9 | 1.673 868 4 | 1.000 000 0 | 6.000 000 0 | 8357 |
| | | gender | 1.680 268 0 | 0.466 400 5 | 1.000 000 0 | 2.000 000 0 | 8357 |
| | | race | 1.137 010 9 | 0.609 495 1 | 0 | 6.000 000 0 | 8357 |
| | | beneficiarycounty | 380.996 888 8 | 268.622 989 8 | 0 | 999.000 000 0 | 8357 |
| | | beneficiarystate | 25.592 198 2 | 15.016 618 4 | 1.000 000 0 | 65.000 000 0 | 8357 |
| | | provider | 145.632 120 6 | 202.655 372 2 | 1.000 000 0 | 1379.00 | 8356 |
| | | lengthofstay | 5.547 391 1 | 2.955 813 3 | 1.000 000 0 | 60.000 000 0 | 8356 |
| | | chf | 0.010 051 5 | 0.099 757 8 | 0 | 1.000 000 0 | 8357 |
| | | valve | 0.027 043 2 | 0.162 219 0 | 0 | 1.000 000 0 | 8357 |
| | | pulmicirc | 0.000 239 320 | 0.015 469 1 | 0 | 1.000 000 0 | 8357 |
| | | perivasc | 0.015 675 5 | 0.124 224 0 | 0 | 1.000 000 0 | 8357 |
| | | htn | 0.060 189 1 | 0.237 851 0 | 0 | 1.000 000 0 | 8357 |
| | | htncx | 0.031 949 3 | 0.175 875 6 | 0 | 1.000 000 0 | 8357 |
| | | para | 0.006 940 3 | 0.083 023 8 | 0 | 1.000 000 0 | 8357 |
| | | neuro | 0.029 795 4 | 0.170 032 6 | 0 | 1.000 000 0 | 8357 |
| | | chrnlung | 0.034 940 8 | 0.183 640 8 | 0 | 1.000 000 0 | 8357 |
| | | dm | 0.013 760 9 | 0.116 504 0 | 0 | 1.000 000 0 | 8357 |
| | | dmcx | 0.014 359 2 | 0.118 973 6 | 0 | 1.000 000 0 | 8357 |
| | | hypothy | 0.045 829 8 | 0.209 128 4 | 0 | 1.000 000 0 | 8357 |

**Table 15.** Continued

| novelrisk | N Obs | Variable | Mean | Std Dev | Minimum | Maximum | N |
|---|---|---|---|---|---|---|---|
| | | renfail | 0.029 675 7 | 0.169 701 3 | 0 | 1.000 000 0 | 8357 |
| | | liver | 0.001 914 6 | 0.043 716 4 | 0 | 1.000 000 0 | 8357 |
| | | ulcer | 0.000 598 301 | 0.024 454 3 | 0 | 1.000 000 0 | 8357 |
| | | aids | 0 | 0 | 0 | 0 | 8357 |
| | | lymph | 0.000 478 641 | 0.021 873 9 | 0 | 1.000 000 0 | 8357 |
| | | mets | 0.001 076 9 | 0.032 801 1 | 0 | 1.000 000 0 | 8357 |
| | | tumor | 0.002 632 5 | 0.051 243 6 | 0 | 1.000 000 0 | 8357 |
| | | arth | 0.006 940 3 | 0.083 023 8 | 0 | 1.000 000 0 | 8357 |
| | | coag | 0.005 384 7 | 0.073 187 1 | 0 | 1.000 000 0 | 8357 |
| | | obese | 0.025 846 6 | 0.158 687 0 | 0 | 1.000 000 0 | 8357 |
| | | wghtloss | 0.004 188 1 | 0.064 583 8 | 0 | 1.000 000 0 | 8357 |
| | | lytes | 0.041 163 1 | 0.198 679 2 | 0 | 1.000 000 0 | 8357 |
| | | bldloss | 0.002 871 8 | 0.053 515 8 | 0 | 1.000 000 0 | 8357 |
| | | anemdef | 0.039 607 5 | 0.195 046 9 | 0 | 1.000 000 0 | 8357 |
| | | alcohol | 0.002 871 8 | 0.053 515 8 | 0 | 1.000 000 0 | 8357 |
| | | drug | 0.000 478 641 | 0.021 873 9 | 0 | 1.000 000 0 | 8357 |
| | | psych | 0.004 307 8 | 0.065 496 0 | 0 | 1.000 000 0 | 8357 |
| | | depress | 0.033 624 5 | 0.180 271 4 | 0 | 1.000 000 0 | 8357 |
| | | htnc | 0.092 138 3 | 0.289 238 4 | 0 | 1.000 000 0 | 8357 |
| | | elixreadmscore | 2.303 697 5 | 6.910 104 7 | -4.000 000 0 | 77.000 000 0 | 8357 |
| | | elixmortalscore | 0.651 071 0 | 3.743 776 1 | -16.000 000 0 | 45.000 000 0 | 8357 |
| | | elixreadmrisk | 0.990 307 5 | 0.097 977 9 | 0 | 1.000 000 0 | 8357 |
| | | elixmortalrisk | 0.999 401 7 | 0.024 454 3 | 0 | 1.000 000 0 | 8357 |
| | | admissiontype | 1.913 007 1 | 1.081 955 0 | 1.000 000 0 | 9.000 000 0 | 8357 |
| | | sourceofadmission | 1.389 682 1 | 1.021 388 3 | 1.000 000 0 | 9.000 000 0 | 8335 |

**Table 15.** Continued

| novelrisk | N Obs | Variable | Mean | Std Dev | Minimum | Maximum | N |
|---|---|---|---|---|---|---|---|
| 1 | 65830 | claimpayment | 11 945.64 | 4850.30 | 0 | 110 451.47 | 65 830 |
| | | providerstate | 25.809 129 6 | 15.132 311 1 | 1.000 000 0 | 65.000 000 0 | 65 830 |
| | | organizationphysician | 1 495 721 087 | 285 582 590 | 1 003 067 648 | 1 992 947 968 | 65 827 |
| | | attendingphysician | 1 501 304 267 | 291 411 973 | 1 003 000 128 | 1 992 998 656 | 65 827 |
| | | operatingphysician | 1 500 661 241 | 291 583 491 | 1 003 001 792 | 1 992 989 056 | 65 827 |
| | | drg | 469.963 90 70 | 0.186 522 9 | 469.000 000 0 | 470.000 000 0 | 65 830 |
| | | drgoutlierstay | 0.380 373 7 | 1.496 878 5 | 0 | 8.000 000 0 | 65 830 |
| | | agegroup | 3.137 399 4 | 1.401 113 8 | 1.000 000 0 | 6.000 000 0 | 65 830 |
| | | gender | 1.630 700 3 | 0.482 618 9 | 1.000 000 0 | 2.000 000 0 | 65 830 |
| | | race | 1.151 724 1 | 0.648 734 7 | 0 | 6.000 000 0 | 65 830 |
| | | beneficiarycounty | 376.864 195 7 | 269.776 657 1 | 0 | 999.000 000 0 | 65 830 |
| | | beneficiarystate | 25.865 319 8 | 15.096 720 8 | 1.000 000 0 | 65.000 000 0 | 65 830 |
| | | provider | 166.120 740 7 | 264.695 832 3 | 1.000 000 0 | 1384.00 | 65 827 |
| | | lengthofstay | 3.916 573 0 | 1.665 624 9 | 1.000 000 0 | 50.000 000 0 | 65 830 |
| | | chf | 0.002 081 1 | 0.045 572 1 | 0 | 1.000 000 0 | 65 830 |
| | | valve | 0.010 891 7 | 0.103 794 1 | 0 | 1.000 000 0 | 65 830 |
| | | pulmicirc | 0.000 151 906 | 0.012 324 2 | 0 | 1.000 000 0 | 65 830 |
| | | perivasc | 0.006 197 8 | 0.078 482 2 | 0 | 1.000 000 0 | 65 830 |
| | | htn | 0.024 244 3 | 0.153 807 8 | 0 | 1.000 000 0 | 65 830 |
| | | htncx | 0.010 633 4 | 0.102 569 7 | 0 | 1.000 000 0 | 65 830 |
| | | para | 0.001 655 8 | 0.040 657 9 | 0 | 1.000 000 0 | 65 830 |
| | | neuro | 0.010 815 7 | 0.103 435 6 | 0 | 1.000 000 0 | 65 830 |
| | | chrnlung | 0.020 340 3 | 0.141 162 5 | 0 | 1.000 000 0 | 65 830 |
| | | dm | 0.010 436 0 | 0.101 622 9 | 0 | 1.000 000 0 | 65 830 |
| | | dmcx | 0.006 213 0 | 0.078 577 8 | 0 | 1.000 000 0 | 65 830 |
| | | hypothy | 0.023 545 5 | 0.151 629 3 | 0 | 1.000 000 0 | 65 830 |

**Table 15.** Continued

| novelrisk | N Obs | Variable | Mean | Std Dev | Minimum | Maximum | N |
|---|---|---|---|---|---|---|---|
| | | renfail | 0.011 013 2 | 0.104 365 2 | 0 | 1.000 000 0 | 65 830 |
| | | liver | 0.001 595 0 | 0.039 906 1 | 0 | 1.000 000 0 | 65 830 |
| | | ulcer | 0.000 486 101 | 0.022 042 5 | 0 | 1.000 000 0 | 65 830 |
| | | aids | 0.000 015 191 | 0.003 897 5 | 0 | 1.000 000 0 | 65 830 |
| | | lymph | 0.000 562 054 | 0.023 701 2 | 0 | 1.000 000 0 | 65 830 |
| | | mets | 0.000 045 572 | 0.006 750 6 | 0 | 1.000 000 0 | 65 830 |
| | | tumor | 0.000 577 244 | 0.024 019 2 | 0 | 1.000 000 0 | 65 830 |
| | | arth | 0.005 650 9 | 0.074 960 5 | 0 | 1.000 000 0 | 65 830 |
| | | coag | 0.001 944 4 | 0.044 052 8 | 0 | 1.000 000 0 | 65 830 |
| | | obese | 0.045 237 7 | 0.207 826 7 | 0 | 1.000 000 0 | 65 830 |
| | | wghtloss | 0.000 592 435 | 0.024 333 0 | 0 | 1.000 000 0 | 65 830 |
| | | lytes | 0.011 393 0 | 0.106 128 9 | 0 | 1.000 000 0 | 65 830 |
| | | bldloss | 0.001 245 6 | 0.035 271 8 | 0 | 1.000 000 0 | 65 830 |
| | | anemdef | 0.014 127 3 | 0.118 016 6 | 0 | 1.000 000 0 | 65 830 |
| | | alcohol | 0.001 974 8 | 0.044 395 0 | 0 | 1.000 000 0 | 65 830 |
| | | drug | 0.000 470 910 | 0.021 695 5 | 0 | 1.000 000 0 | 65 830 |
| | | psych | 0.002 901 4 | 0.053 787 0 | 0 | 1.000 000 0 | 65 830 |
| | | depress | 0.021 494 8 | 0.145 027 8 | 0 | 1.000 000 0 | 65 830 |
| | | htnc | 0.034 877 7 | 0.183 471 4 | 0 | 1.000 000 0 | 65 830 |
| | | elixreadmscore | 0.846 559 3 | 4.051 655 5 | -4.000 000 0 | 78.000 000 0 | 65 830 |
| | | elixmortalscore | -0.044 782 0 | 2.160 176 5 | -16.000 000 0 | 43.000 000 0 | 65 830 |
| | | elixreadmrisk | 0.997 888 5 | 0.045 902 9 | 0 | 1.000 000 0 | 65 830 |
| | | elixmortalrisk | 0.999 939 2 | 0.007 794 9 | 0 | 1.000 000 0 | 65 830 |
| | | admissiontype | 2.852 772 3 | 0.535 952 7 | 1.000 000 0 | 9.000 000 0 | 65 830 |
| | | sourceofadmission | 1.338 202 0 | 0.657 075 8 | 1.000 000 0 | 9.000 000 0 | 65 727 |

Logistic Regression (LR) was run using SAS EG using a binary logit model with the Fisher's scoring optimization technique (the results are displayed in Table 16 and Figure 9 below). The number of response levels are two with the response profile of novel risk = 0 (8333) or 1 (65 724). There were 74 187 beneficiary claims read, but only 74 057 beneficiary claims used; 130 claims were deleted due to explanatory variables. The probability modeled is novel risk = 0. The model converged satisfactorily using the gradient convergence criterion. The Deviance, Pearson, and Hosmer-Lemeshow goodness-of-fit tests show p-values less than .05, which brings the model into question. The model fit statistics used two criterion: Akaike Information Criterion and Schwarz Criterion. In the Testing Global Null Hypothesis: BETA=0, likelihood ratio, Score, and Wald test that a predictor's coefficient is not zero. The Receiver Operating Curve for this model is 0.7758 with this sample.

**Table 16.** Logistic Regression Results: The LOGISTIC Procedure

| Model Information | |
|---|---|
| Response Variable | novelrisk |
| Number of Response Levels | 2 |
| Model | binary logit |
| Optimization Technique | Fisher's scoring |

| | |
|---|---|
| Number of Observations Read | 74 187 |
| Number of Observations Used | 74 057 |

| Response Profile | | |
|---|---|---|
| Ordered Value | novelrisk | Total Frequency |
| 1 | 0 | 8333 |
| 2 | 1 | 65 724 |

**Table 16.** Continued

Probability modeled is novelrisk=0.

| Model Convergence Status |
|---|
| Convergence criterion (GCONV=1E-8) satisfied. |

| Deviance and Pearson Goodness-of-Fit Statistics | | | | |
|---|---|---|---|---|
| Criterion | Value | DF | Value/DF | Pr > ChiSq |
| Deviance | 40 155.1044 | 73E3 | 0.5481 | 1.0000 |
| Pearson | 285 142.619 | 73E3 | 3.8921 | <.0001 |

Number of unique profiles: 73311

| Model Fit Statistics | | |
|---|---|---|
| Criterion | Intercept Only | Intercept and Covariates |
| AIC | 52 101.803 | 40 641.402 |
| SC | 52 111.016 | 41 102.032 |
| -2 Log L | 52 099.803 | 40 541.402 |

| Testing Global Null Hypothesis: BETA=0 | | | |
|---|---|---|---|
| Test | Chi-Square | DF | Pr > ChiSq |
| Likelihood Ratio | 11 558.4010 | 49 | <.0001 |
| Score | 15 421.6452 | 49 | <.0001 |
| Wald | 10 733.3425 | 49 | <.0001 |

| Hosmer and Lemeshow Goodness-of-Fit Test | | |
|---|---|---|
| Chi-Square | DF | Pr > ChiSq |
| 332.7789 | 8 | <.0001 |

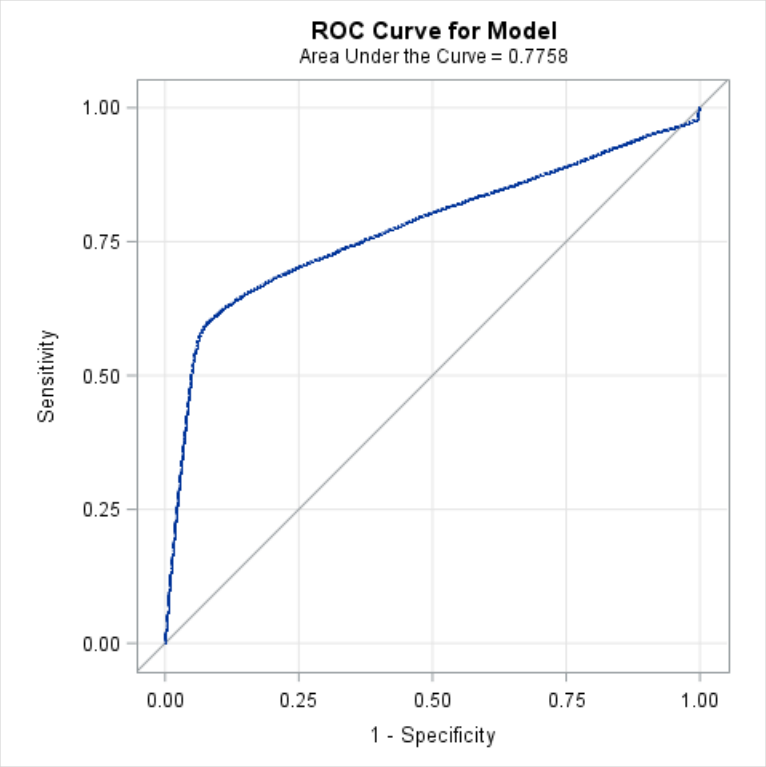



**Figure 9.** Logistic Regression Results: ROC Curve

Table 17 displays the key utilization and quality metrics used to measure quality of care in an inpatient stay, including length of stay, 90-day readmission, emergency room visit, and mortality.

**Table 17.** Utilization and Quality Metrics

| Characteristics | DRG 469 | DRG 470 |
|---|---|---|
| length of stay mean(sd) | 7.8(4.6) | 3.9(1.4) |
| quality metrics, % | | |
| inpatient stays 90-day readmission | 0.62 | 1.29 |
| inpatient stays with an ER visit | 34.29 | 8.65 |
| inpatient stays where patient died | 4.62 | 0.06 |

## 4.2 Elixhauser Comorbidity Index

The Elixhauser Comorbidity Index was used to decipher up to twenty-five ICD codes for each claim. The codes were categorized into 29 different comorbidity areas and subsequently used to calculate a mortality and readmission index. It has been shown that the measures used by Elixhauser are strongly connected with inpatient mortality. Van Walraven et al's[99] findings show Elixhauser Comorbidity Index can be an effective determinant for inpatient mortality. Additionally, Sharabiani et al[100] found that Elixhauser index is well suited to predict risk when inpatient hospitalization is greater than 30 days. Table 18 presents the mean and standard deviation for the sample regarding each of the 29 comorbidities.

**Table 18.** Means of Comorbidity Variables

| Variable | Label | N | N Miss | Mean | Std Dev | Min. | Max. |
|---|---|---|---|---|---|---|---|
| CHF | Congestive heart failure | 74 187 | 0 | 0.033 280 8 | 0.179 37 | 0 | 1 |
| VALVE | Valvular disease | 74 187 | 0 | 0.035 491 4 | 0.185 019 5 | 0 | 1 |
| PULMCIRC | Pulmonary circulation disease | 74 187 | 0 | 0.011 592 3 | 0.107 042 5 | 0 | 1 |
| PERIVASC | Peripheral vascular disease | 74 187 | 0 | 0.022 645 5 | 0.148 771 5 | 0 | 1 |
| HTN_C | Hypertension | 74 187 | 0 | 0.467 359 5 | 0.498 936 8 | 0 | 1 |
| PARA | Paralysis | 74 187 | 0 | 0.004 003 4 | 0.063 146 | 0 | 1 |
| NEURO | Other neurological disorders | 74 187 | 0 | 0.045 264 | 0.207 884 | 0 | 1 |
| CHRNLUNG | Chronic pulmonary disease | 74 187 | 0 | 0.109 709 2 | 0.312 529 1 | 0 | 1 |
| DM | Diabetes w/o chronic complications | 74 187 | 0 | 0.124 873 6 | 0.330 577 8 | 0 | 1 |
| DMCX | Diabetes w/ chronic complications | 74 187 | 0 | 0.012 266 3 | 0.110 072 7 | 0 | 1 |
| HYPOTHY | Hypothyroidism | 74 187 | 0 | 0.125 547 6 | 0.331 341 | 0 | 1 |
| RENLFAIL | Renal failure | 74 187 | 0 | 0.051 707 2 | 0.221 436 7 | 0 | 1 |
| LIVER | Liver disease | 74 187 | 0 | 0.006 524 1 | 0.080 508 2 | 0 | 1 |
| ULCER | Peptic ulcer Disease w/ bleeding | 74 187 | 0 | 0.000 094 356 | 0.009 713 3 | 0 | 1 |
| AIDS | Acquired immune deficiency syndrome | 74 187 | 0 | 0.000 256 11 | 0.016 001 5 | 0 | 1 |
| LYMPH | Lymphoma | 74 187 | 0 | 0.003 059 8 | 0.055 231 5 | 0 | 1 |
| METS | Metastatic cancer | 74 187 | 0 | 0.002 210 6 | 0.046 965 7 | 0 | 1 |
| TUMOR | Solid tumor w/out metastasis | 74 187 | 0 | 0.004 893 | 0.069 779 4 | 0 | 1 |
| ARTH | Rheumatoid arthritis/collagen vas | 74 187 | 0 | 0.031 501 5 | 0.174 669 8 | 0 | 1 |
| COAG | Coagulopathy | 74 187 | 0 | 0.018 979 1 | 0.136 451 9 | 0 | 1 |
| OBESE | Obesity | 74 187 | 0 | 0.113 604 8 | 0.317 332 8 | 0 | 1 |
| WGHTLOSS | Weight loss | 74 187 | 0 | 0.006 955 4 | 0.083 109 | 0 | 1 |
| LYTES | Fluid and electrolyte disorders | 74 187 | 0 | 0.081 941 6 | 0.274 277 5 | 0 | 1 |

**Table 18.** Continued

| Variable | Label | N | N Miss | Mean | Std Dev | Min. | Max. |
|---|---|---|---|---|---|---|---|
| BLDLOSS | Chronic blood loss anemia | 74 187 | 0 | 0.007 845 | 0.088 224 7 | 0 | 1 |
| ANEMDEF | Deficiency Anemias | 74 187 | 0 | 0.085 109 3 | 0.279 046 1 | 0 | 1 |
| ALCOHOL | Alcohol abuse | 74 187 | 0 | 0.007 737 2 | 0.087 621 | 0 | 1 |
| DRUG | Drug abuse | 74 187 | 0 | 0.003 545 1 | 0.059 435 5 | 0 | 1 |
| PSYCH | Psychoses | 74 187 | 0 | 0.017 226 7 | 0.130 116 1 | 0 | 1 |
| DEPRESS | Depression | 74 187 | 0 | 0.091 673 7 | 0.288 566 8 | 0 | 1 |

The following four figures present the results for all of the studied comorbidities broken down into categories. Figure 10 shows comorbidities by gender and DRG. Given that DRG 469 is major joint replacement or reattachment of lower extremity with major complications or comorbidity (MCC), higher counts under this DRG are expected. Notably in Figure 10, females under DRG 469 had the highest frequency of obese comorbidity (1981), which is almost double the frequency of males (1079) under DRG 469. The highest frequencies of comorbidity associated with MJR with MCC for both females and males were obesity and hypertension. Additionally, hypothyroidism and depression were almost 400% higher in females than in males for DRG 469. In Figure 11, those falling under the Race category of white had the highest frequency of comorbidities. Figure 12 graphically displays the comorbidities by count for this sample, and clearly shows obesity and hypertension as the comorbidities with the highest frequency. Finally, Figure 13 shows Asians under 64 and over 85 as having the highest claim payments, with female claim payments being the highest.

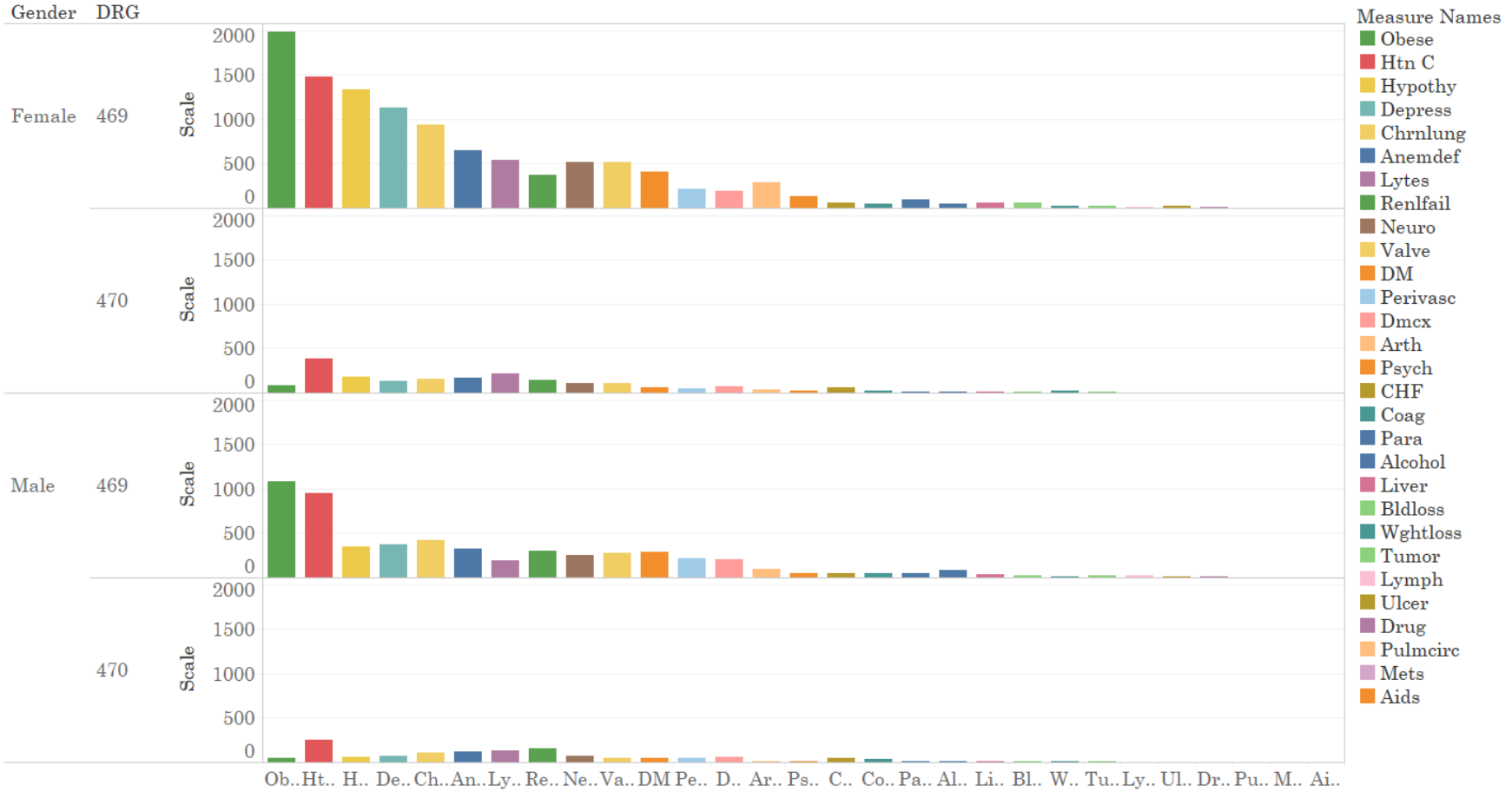



**Figure 10.** Prevalence of Comorbidities by Gender & DRG

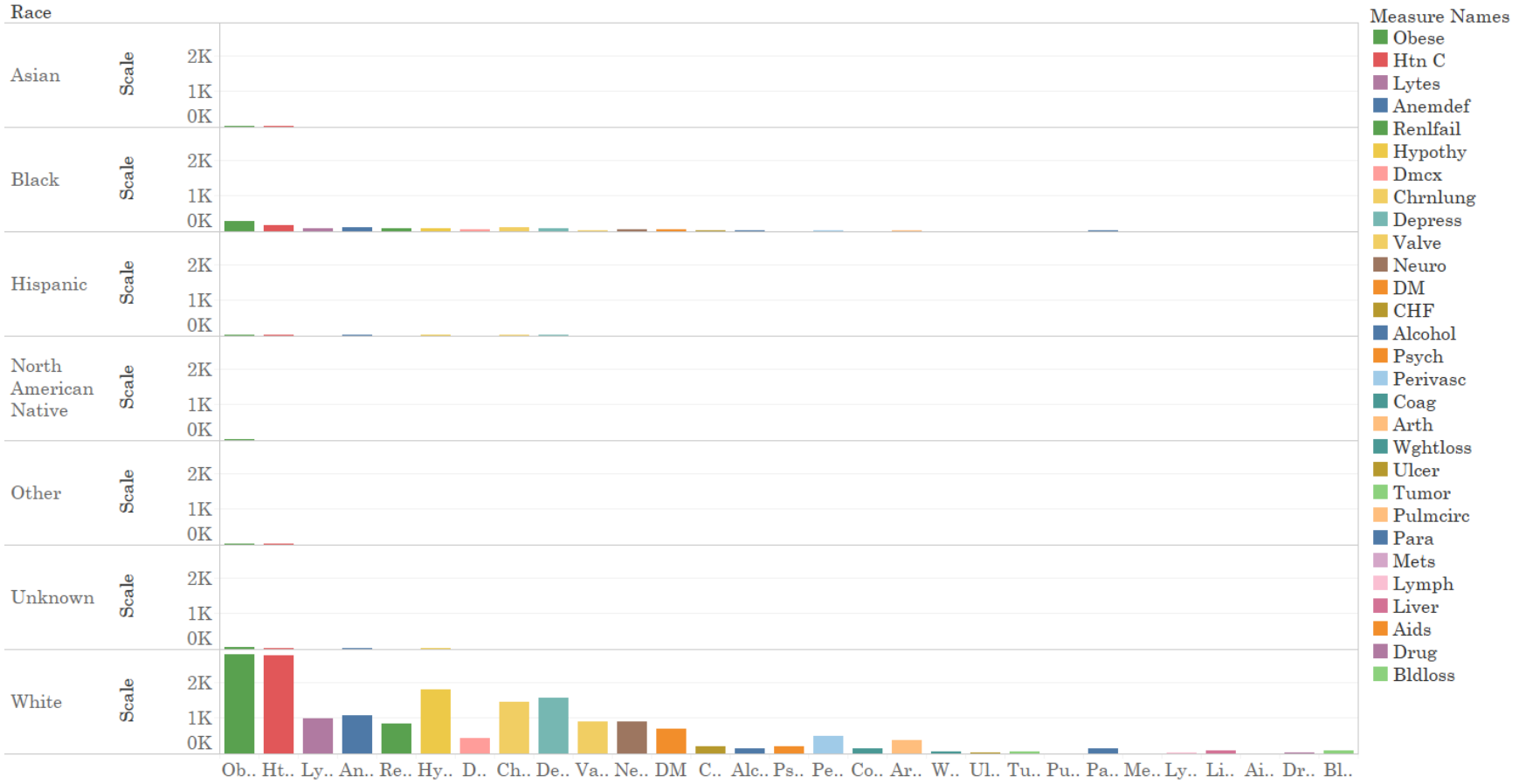



**Figure 11.** Prevalence of Comorbidities by Race

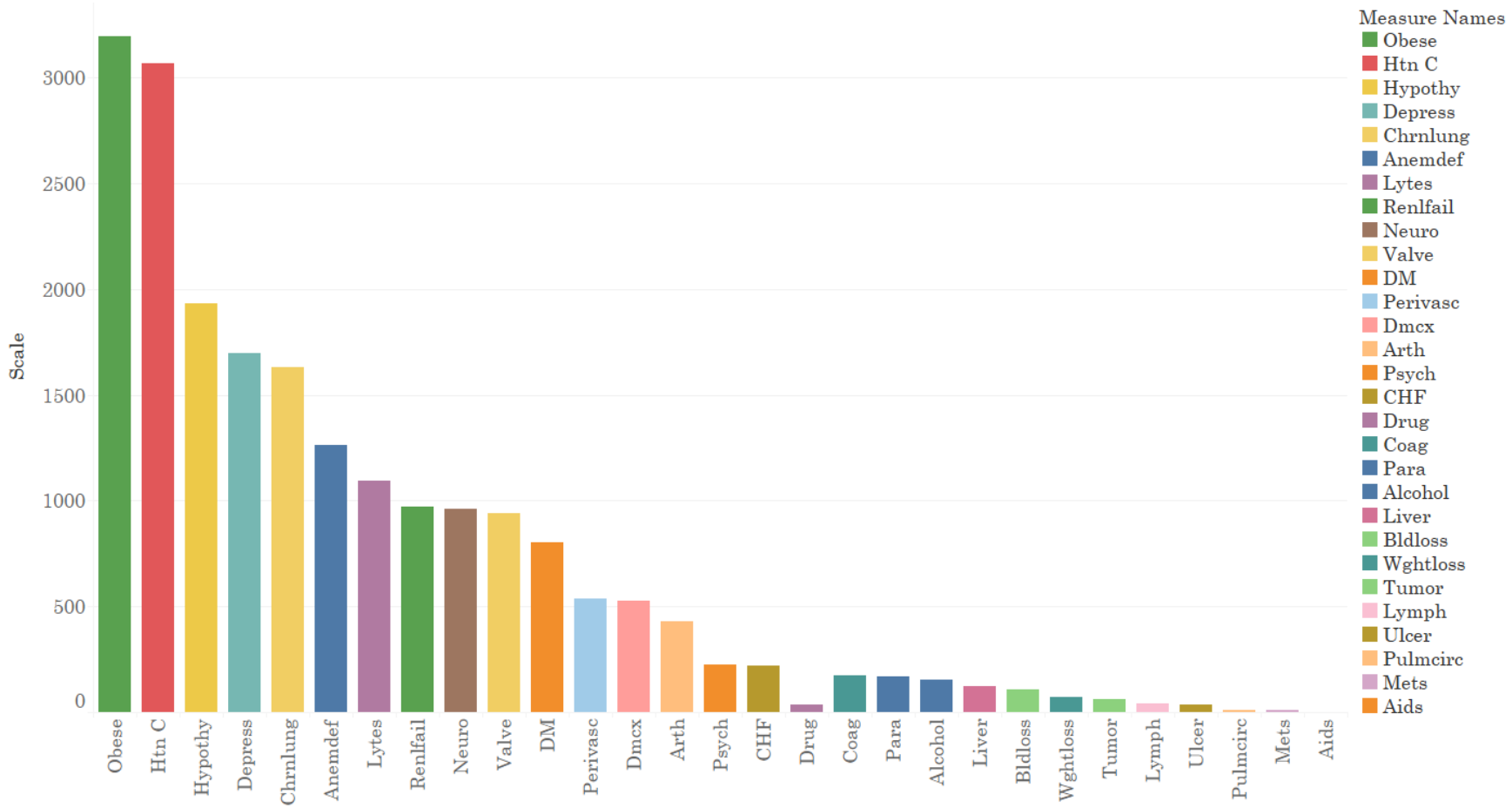



**Figure 12.** Comorbidities by Count

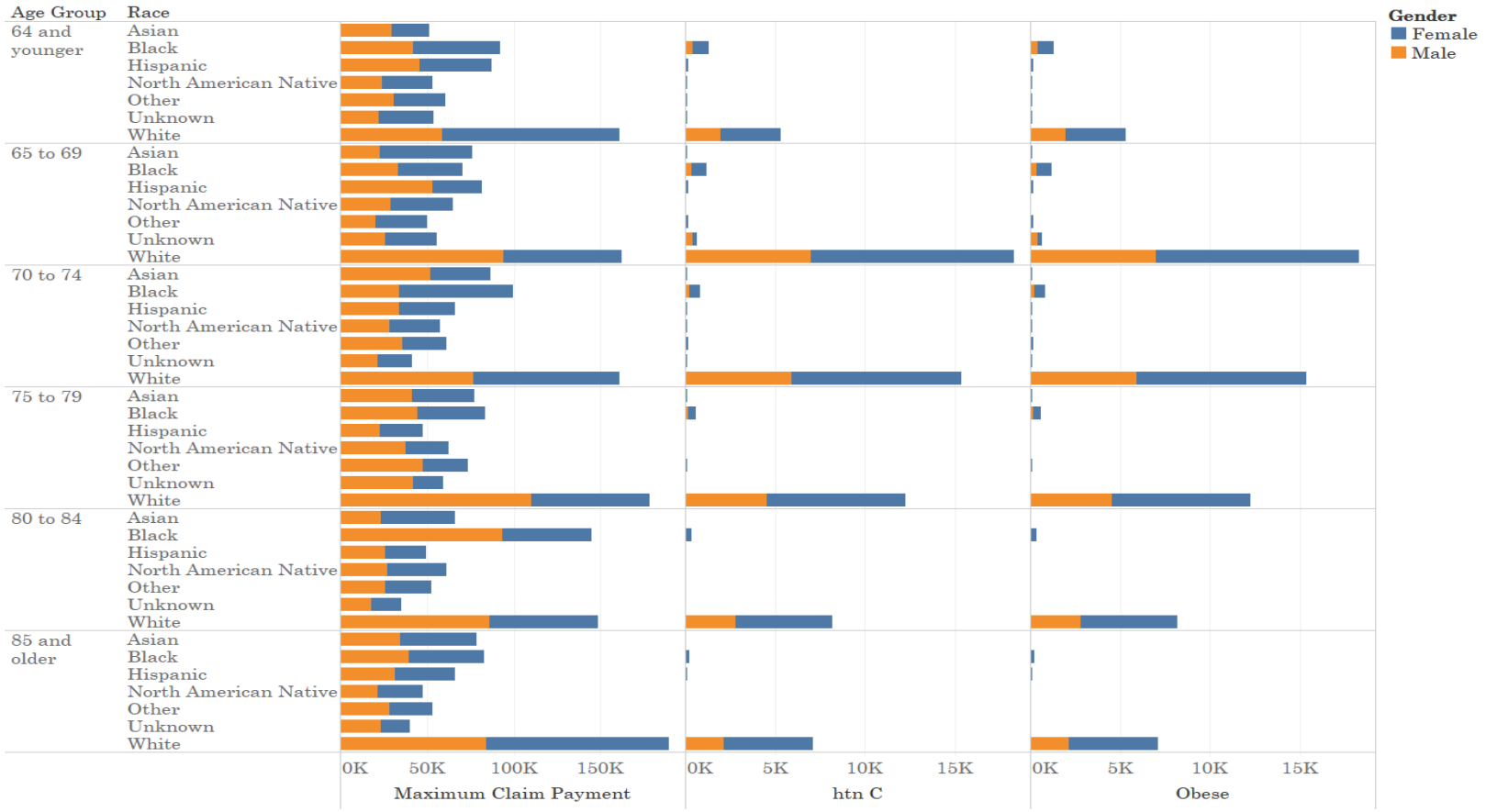



**Figure 13.** Age, Race by Average Medicare Claim Payments within Gender

## 4.3 Features

The features listed below in Table 19 were the baseline set of features selected from the inpatient claims. They are the independent variables used as predictors in this research.

**Table 19.** Selected Baseline Features from the Inpatient Claims Sample

| Features | Variable | Used As |
|---|---|---|
| Access | | |
| provider | independent | predictor |
| provider state | independent | predictor |
| attending physician | independent | predictor |
| operating physician | independent | predictor |
| organization physician | independent | predictor |
| beneficiary state | independent | predictor |
| beneficiary county | independent | predictor |
| age group | independent | predictor |
| race | independent | predictor |
| gender | independent | predictor |
| source of admission | independent | predictor |
| type of admission | independent | predictor |
| Comorbidities | | |
| congestive heart failure | independent | predictor |
| valvular disease | independent | predictor |
| pulmonary circulation disease | independent | predictor |
| peripheral vascular disease | independent | predictor |
| hypertension crisis | independent | predictor |
| paralysis | independent | predictor |
| other neurological disorders | independent | predictor |
| chronic pulmonary disease | independent | predictor |
| diabetes without chronic | independent | predictor |
| Complications | | |
| diabetes with chronic complications | independent | predictor |
| hypothyroidism | independent | predictor |
| renal failure | independent | predictor |
| liver disease | independent | predictor |
| peptic ulcer disease with bleeding | independent | predictor |

**Table 19.** Continued

| | | |
|---|---|---|
| hypothyroidism | independent | predictor |
| acquired immune deficiency Syndrome | independent | predictor |
| lymphoma | independent | predictor |
| metastatic cancer | independent | predictor |
| solid tumor w/out metastasis | independent | predictor |
| rheumatoid arthritis | independent | predictor |
| coagulopathy | independent | predictor |
| obesity | independent | predictor |
| weight loss | independent | predictor |
| fluid and electrolyte disorder | independent | predictor |
| chronic blood loss anemia | independent | predictor |
| deficiency anemias | independent | predictor |
| alcohol abuse | independent | predictor |
| drug abuse | independent | predictor |
| psychoses | independent | predictor |
| Cost | | |
| payment amount | independent | predictor |
| Utilization | | |
| drg | independent | predictor |
| drg outlier stay | independent | predictor |
| drg weight | independent | predictor |
| length of stay | independent | predictor |
| elixhauser readmission risk | independent | predictor |
| elixhauser mortality risk | independent | predictor |
| elixhauser readmission index score | independent | predictor |
| elixhauser mortality index score | independent | predictor |

## 4.4 Imputation

Imputation was used to address missing values for both class and nominal variables in the dataset prior to running algorithms against it. The impute method used for class variables was the 'count' setting, which used the value in the class variable under test that had the highest occurrence. The nominal variable was imputed by replacing missing values with the mean of the variable under test.

Indicator and unique binary variables were used to identify the variables that had been imputed. Additionally, indicator variables were assigned the role of 'input' rather than rejection of the observation. Table 20 shows the variables that were imputed, method, value used, and how many times imputation was used for the imputed variable. One Hot Encoding was selected for categorical variables using the MLJAR machine learning platform in order to raise the effectiveness of the machine learning algorithms to predict.

**Table 20.** Imputation

| Imputed Variable | Method | Value Used | Occurrences |
|---|---|---|---|
| attending physician | COUNT | 1 639 185 978 | 3 |
| length of stay | MEAN | 4.1 | 1 |
| operating physician | COUNT | 1 639 185 978 | 3 |
| organization physician | COUNT | 1 598 703 019 | 3 |

### 4.5 Data Mining using MATLAB

All algorithms were run on the MATLAB platform using the Classification Learner application, as presented in Table 21. Algorithms were run with their default settings out-of-the-box, as shown in Table 22. Neighborhood Component Analysis (NCA) was run against the training dataset using the fscnca function, given that the predictorImportance function is only available for Tree-based and Ensemble algorithms. Feature weights were ascertained from the fscnca function as seen in Table NCA. The predictorImportance function was used to calculate the influence the predictors have on the response variable and can be viewed in Figures 14–20. Fifteen different algorithms were run consisting of trees, discriminant, SVM, KNN, and ensembles. The Ensemble Boosted Trees and RUSBoosted Trees produced ROCs of 0.80. Additionally, they performed just as well on the test

dataset, recording a ROC of 0.81. The logistic regression yielded the same ROC of 0.77, validating the SAS EG results discussed earlier in this chapter.

**Table 21.** MATLAB Classification Algorithms Used

| Algorithm | Dataset | ROC | ASE |
|---|---|---|---|
| Fine Tree | Train | 0.79 | |
| | Test | 0.79 | 0.0979 |
| Medium Tree | Train | 0.75 | |
| | Test | 0.76 | 0.0960 |
| Coarse Tree | Train | 0.73 | |
| | Test | 0.74 | 0.0966 |
| Linear Discriminant* | Train | 0.78 | |
| | Test | 0.79 | 0.1162 |
| Linear SVM | Train | 0.70 | |
| | Test | 0.73 | 0.1126 |
| Fine Gaussian SVM* | Train | 0.78 | |
| | Test | 0.78 | 0.1023 |
| Medium Gaussian SVM* | Train | 0.77 | |
| | Test | 0.77 | 0.0988 |
| Coarse Gaussian SVM* | Train | 0.75 | |
| | Test | 0.76 | 0.1122 |
| Fine KNN* | Train | 0.63 | |
| | Test | 0.64 | 0.1423 |
| Medium KNN* | Train | 0.77 | |
| | Test | 0.78 | 0.1018 |
| Coarse KNN* | Train | 0.79 | |
| | Test | 0.80 | 0.1011 |
| Cosine KNN* | Train | 0.77 | |
| | Test | 0.78 | 0.1038 |
| Ensemble Boosted Trees | Train | 0.80 | |
| | Test | 0.81 | 0.0965 |
| Ensemble Bagged Trees | Train | 0.79 | |
| | Test | 0.79 | 0.1010 |
| Ensemble RUBoosted Trees | Train | 0.80 | |
| | Test | 0.81 | 0.1154 |

* Predictor importance not available for these algorithms

**Table 22.** Matlab Out-of-the-Box Settings

| Operation— Advanced Tree Options | Max. No. Splits | Split Criterion | Surrogate Decision Splits | Max. Surrogates Per Node |
|---|---|---|---|---|
| Fine Tree | 100 | Gini's Diversity Index | Off | 10 |
| Medium Tree | 20 | Gini's Diversity Index | Off | 10 |
| Coarse Tree | 4 | Gini's Diversity Index | Off | 10 |

| Operation | Covariance Structure |
|---|---|
| Advanced Linear Discriminant Options | Full |

| Operation— Advanced KNN Options | No. Neighbors | Distance Metric | Distance Weight | Standardize Data (Yes/No) |
|---|---|---|---|---|
| Fine KNN | 1 | Euclidean | Equal | Yes |
| Medium KNN | 10 | Euclidean | Equal | Yes |
| Course KNN | 10 | Euclidean | Equal | Yes |
| Cosine KNN | 10 | Cosine | Equal | Yes |

| Operation—Advanced SVM Options | Kernel Function | Box Constraint Level | Kernel Scale Mode | Manual Kernel Scale | Multiclass Method | Standardize Data (Yes/No) |
|---|---|---|---|---|---|---|
| Linear SVM | Linear | 1 | Auto | 1 | One-vs-One | Yes |
| Fine Gaussian SVM | Gaussian | 1 | Manual | 1.8 | One-vs-One | Yes |
| Medium Gaussian SVM | Gaussian | 1 | Manual | 7.2 | One-vs-One | Yes |
| Coarse Gaussian SVM | Gaussian | 1 | Manual | 29 | One-vs-One | Yes |

**Table 22.** Continued

| Operation—Advanced Ensemble Options | Ensemble Method | Learner Type | Max. No. Splits | No. Learners | Learning Rate | Subspace Dimension |
|---|---|---|---|---|---|---|
| Boosted Trees (AdaBoost) | Adaboost | Decision Tree | 20 | 30 | 0.1 | 1 |
| Boosted Trees (Bag) | Bag | Decision Tree | 59 347 | 30 | 0.1 | 1 |
| Boosted Trees RUSBoost) | RUSBoost | Decision Tree | 20 | 30 | 0.1 | 1 |

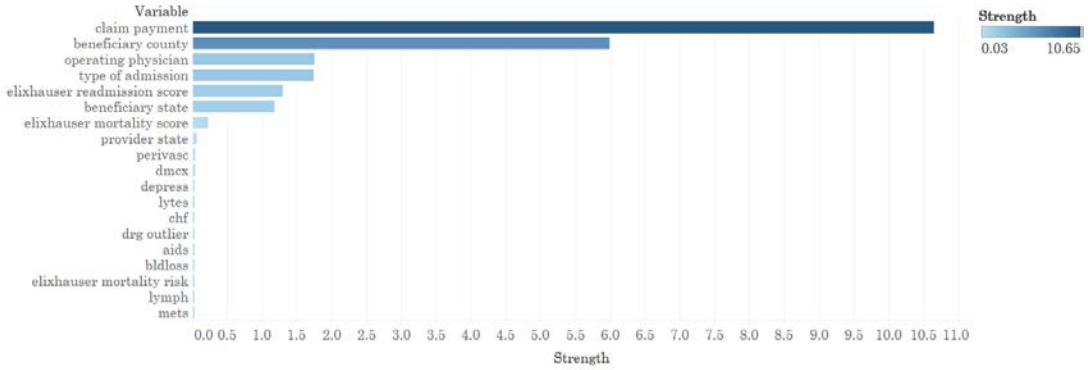



**Figure 14.** Table NCA Neighborhood Component Analysis Feature Selection

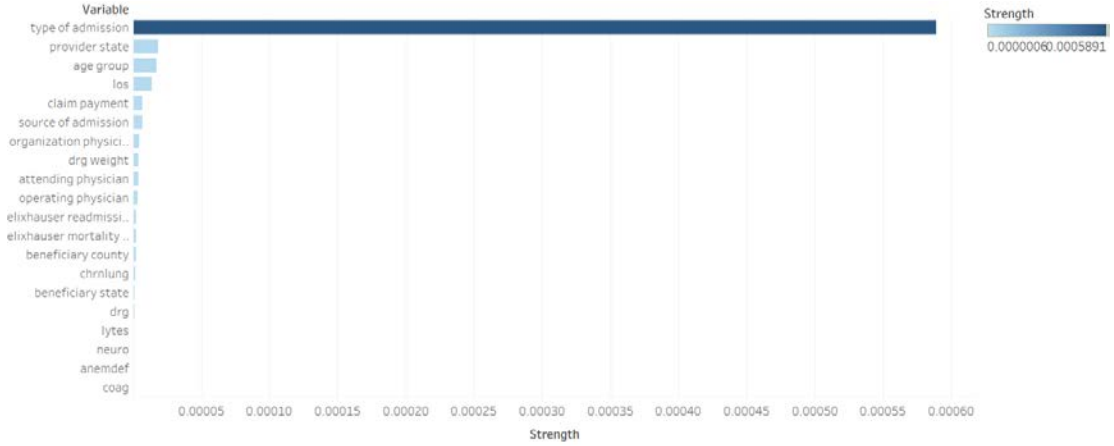



**Figure 15.** Predictors Most Involved in Fine Tree Algorithm

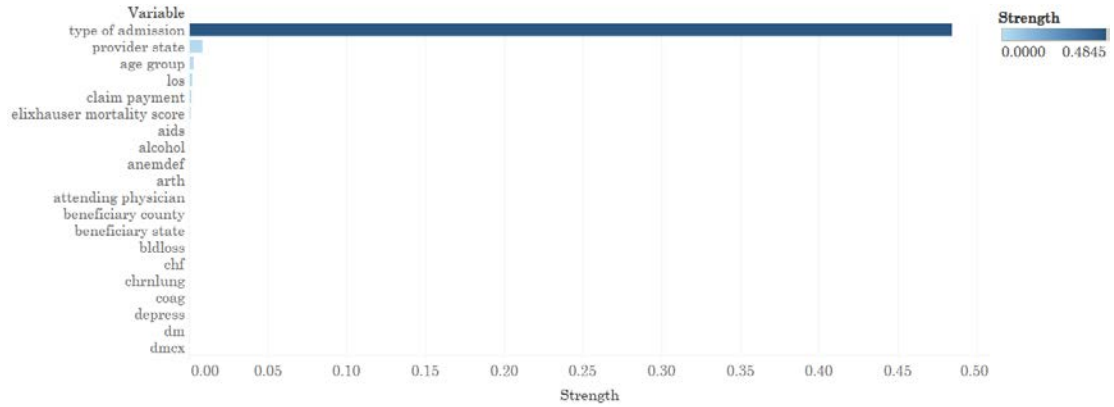



**Figure 16.** Predictors Most Involved in Medium Tree Algorithm

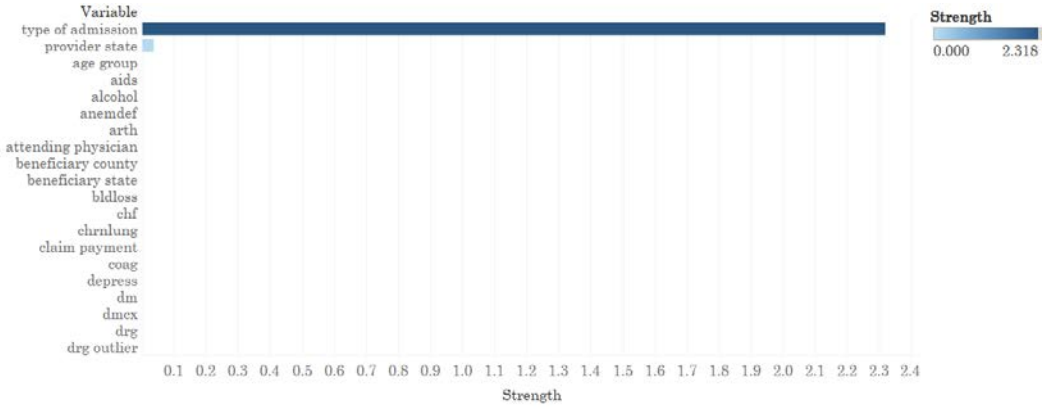



**Figure 17.** Predictors Most Involved in Coarse Tree Algorithm

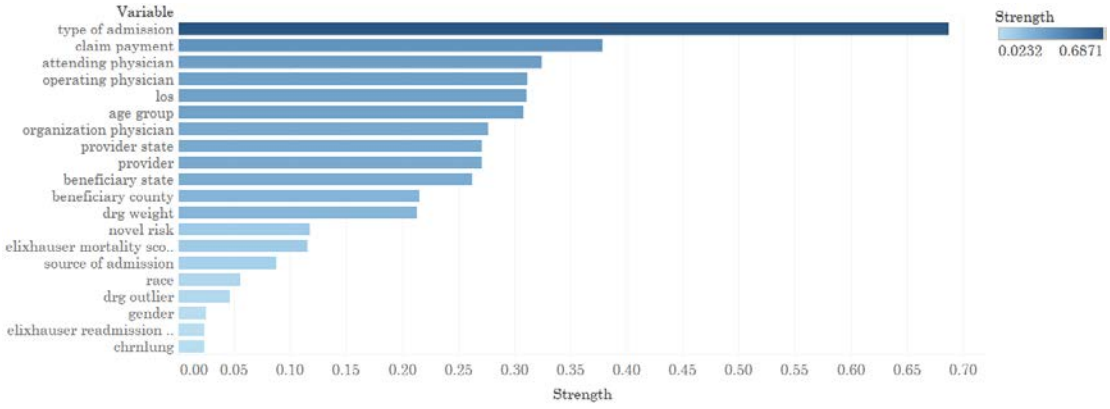



**Figure 18.** Predictors Most Involved in Ensemble Boosted Trees Algorithm

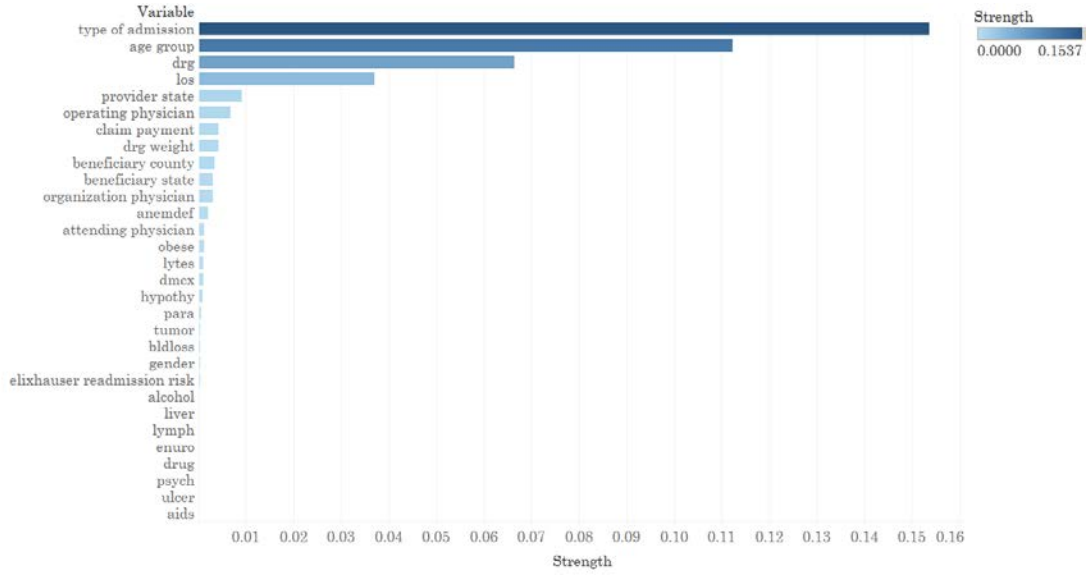



**Figure 19.** Predictors Most Involved in Ensemble Bagged Trees Algorithm

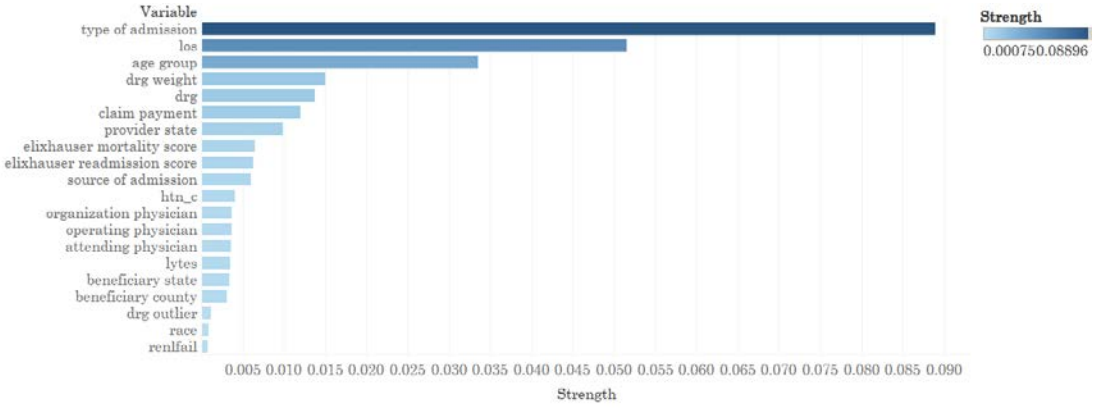



**Figure 20.** Predictors Most Involved in Ensemble RUSBoosted Trees Algorithm

## 4.6 Data Mining using MLJAR

MLJAR offers some of the very latest and highly touted open source algorithms available today, and it can be found on Github and scikit-learn.

Table 23 contains the classification algorithms used on the MLJAR cloud platforms along with their associated receiver operating curve (ROC), standard deviation (Stddev), and variance (Var)—Averaged Squared Error (ASE) and Misclassification Rate (MISC) statistical metrics are not available on the MLJAR platform. However, ASE was calculated from the score data for the training and test datasets. The calculation tested each score: if it was greater than .50, then the predicted class was given a 1; if it was less than .50, then the predicted class was set to zero. The difference between the actual class and predicted class was squared, then the squared values were summed and divided by the number of observations, resulting in the ASE. The published settings for the MLjar algorithms used are presented in Table 24 along with the learning parameters used. It is not known "how" the settings were derived. The categorical columns in the training data were preprocessed using one-hot encoding, and the algorithms learning parameters were time constrained at 5 minutes and 500 maximum steps. LightGBM yielded the best ROC at 0.81, and all five algorithms recorded ROC's between 0.80 and 0.81 for the novel risk dependent variable. XGBoost recorded the best ROC of 0.75 for the Test dataset.

The 20 strongest predictors were captured for each algorithm and are displayed on the following pages. The predictors that were most involved in the LightGBM algorithm are shown in Figure 21. Claim payment, provider, organization physician, attending physician, and operating physician strongly

influenced the outcome variable of novel risk. The predictors that were most involved in the XGBoost algorithm are shown in Figure 22. Again, claim payment, provider, and organization physician came in as the top three influencers, followed by age group, attending physician, operating physician, length of stay, and beneficiary county. All-in-all, these eight predictors accounted for almost 50% of the ROC when predicting the outcome variable of novel risk. Both Random Forest and Extra Trees algorithms, shown in Figure 23 and 24 respectively, recorded type of admission as accounting for most of the ROC when predicting the outcome variable of novel risk. Regularized Greedy Forest in its original implementation does not have tree weight; hence, feature importance cannot be calculated in the regularized greedy forest algorithm.

**Table 23.** MLJAR Classification Algorithms Used (15-Fold CV Training dataset only)

| | Dataset | ROC | Stddev | Var | ASE |
|---|---|---|---|---|---|
| LightGBM | Train | 0.81 | 0.023 199 | 0.000 538 | 0.0981 835 95 |
| | Test | 0.68 | | | 0.095 693 78 |
| XGBoost | Train | 0.80 | 0.020 363 | 0.000 414 | 0.102 042 192 |
| | Test | 0.75 | | | 0.099 804 569 |
| Random Forest | Train | 0.80 | 0.020 363 | 0.000 414 | 0.098 389 379 |
| | Test | 0.67 | | | 0.095 222 05 |
| Regularized Greedy Forest | Train | 0.80 | 0.022 605 | 0.000 511 | 0.099 834 872 |
| | Test | 0.74 | | | 0.095 491 61 |
| Extra Trees | Train | 0.80 | 0.020 725 | 0.000 429 | 0.102 075 89 |
| | Test | 0.62 | | | 0.097 108 97 |

**Table 24.** Published Settings for MLjar Algorithms Used in Research with Learning Parameters

| Algorithm LightGBM | Algorithm Extreme Gradient Boosting | Algorithm Regularized Greedy Forest |
|---|---|---|
| • Trees/Iterations: 250<br>• num_leaves: 64<br>• bagging_freq: 1<br>• metric: ROC<br>• objective: binary<br>• bagging_fraction: 0.7<br>• learning_rate: 0.0075<br>• feature_fraction: 0.6 | • Trees/Iterations: 150<br>• colsample_bytree: 0.7<br>• eval_metric: ROC<br>• min_child_weight: 35<br>• subsample: 0.3<br>• eta: 0.0075<br>• objective: binary:logistic<br>• max_depth: 8<br>• booster: gbtree | • Trees/Iterations: 950<br>• reg_depth: 1<br>• min_pop: 6<br>• reg_L2: 0.1<br>• reg_sL2: 0.001 |
| Preprocessing:<br>• Convert categorical values: One-hot encoding | Preprocessing:<br>• Convert categorical values: One-hot encoding | Preprocessing:<br>• Convert categorical values: One-hot encoding |

| Algorithm Random Forest | Algorithm Extra Trees | Learning Framework Parameters * |
|---|---|---|
| • Trees/Iterations: 115<br>• max_features: 0.2<br>• min_samples_split: 8<br>• criterion: entropy<br>• min_samples_leaf: 17 | • Trees/Iterations: 20<br>• max_features: 0.3<br>• min_samples_split: 15<br>• criterion: gini<br>• min_samples_leaf: 7 | • one_step: 50<br>• train_cant_improve_limit: 5<br>• max_steps: 500<br>• time_constraint: 300 |
| Preprocessing:<br>• Convert categorical values: One-hot encoding | Preprocessing:<br>• Convert categorical values: One-hot encoding | Preprocessing:<br>• Convert categorical values: One-hot encoding |

* Learning Framework Parameters apply to all Algorithms.

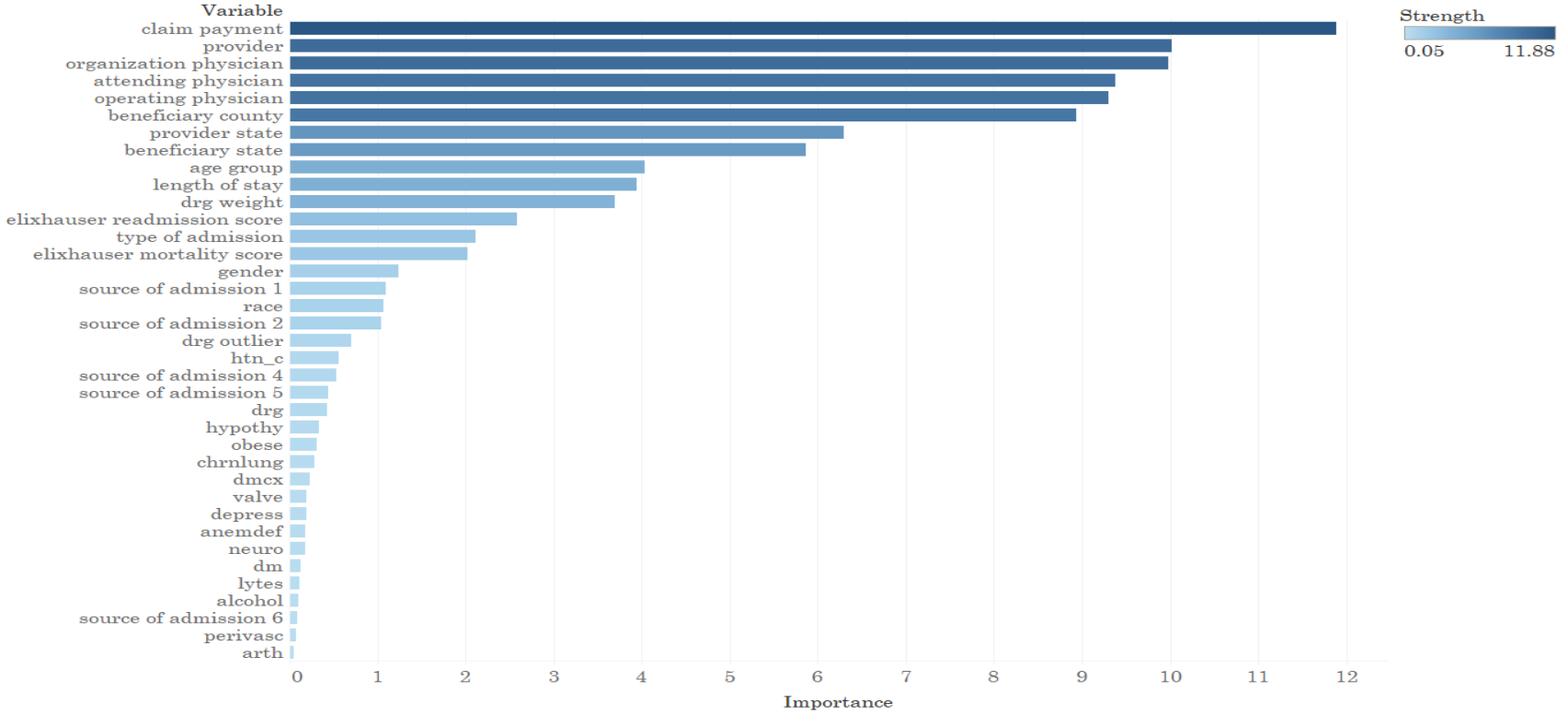



**Figure 21.** Predictors Most Involved in LightGBM Algorithm

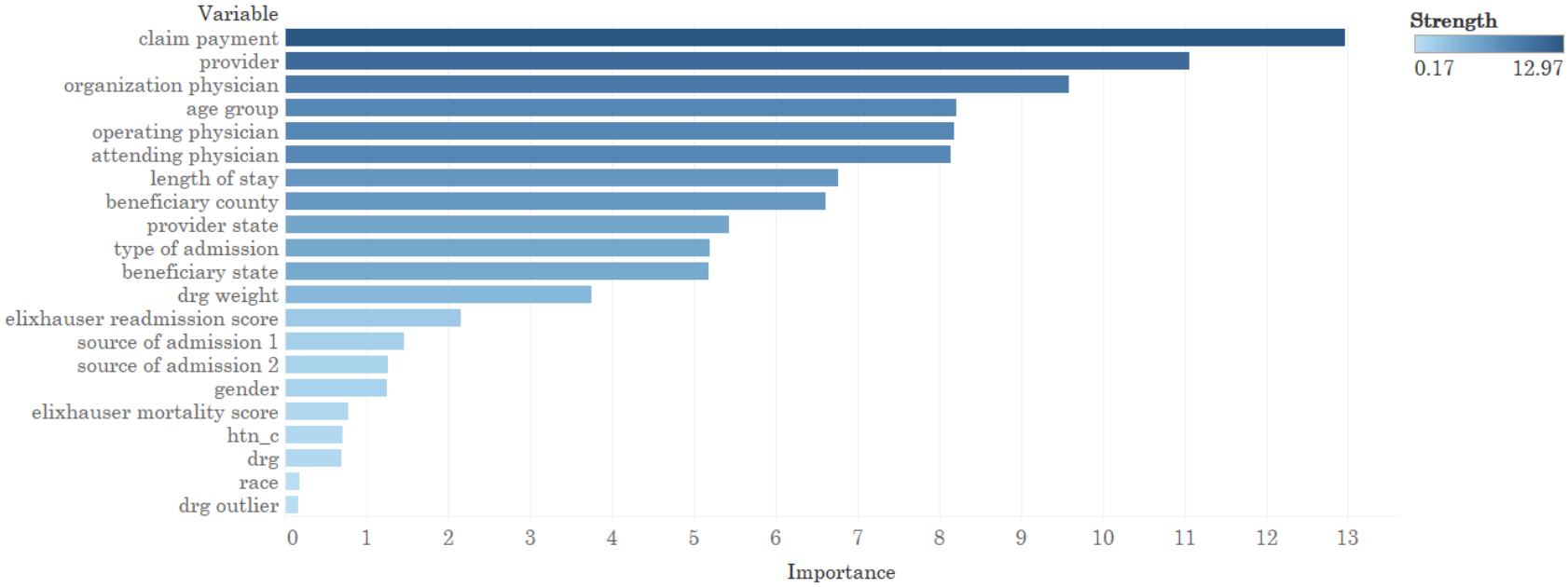



**Figure 22.** Predictors Most Involved in XGBoost Algorithm

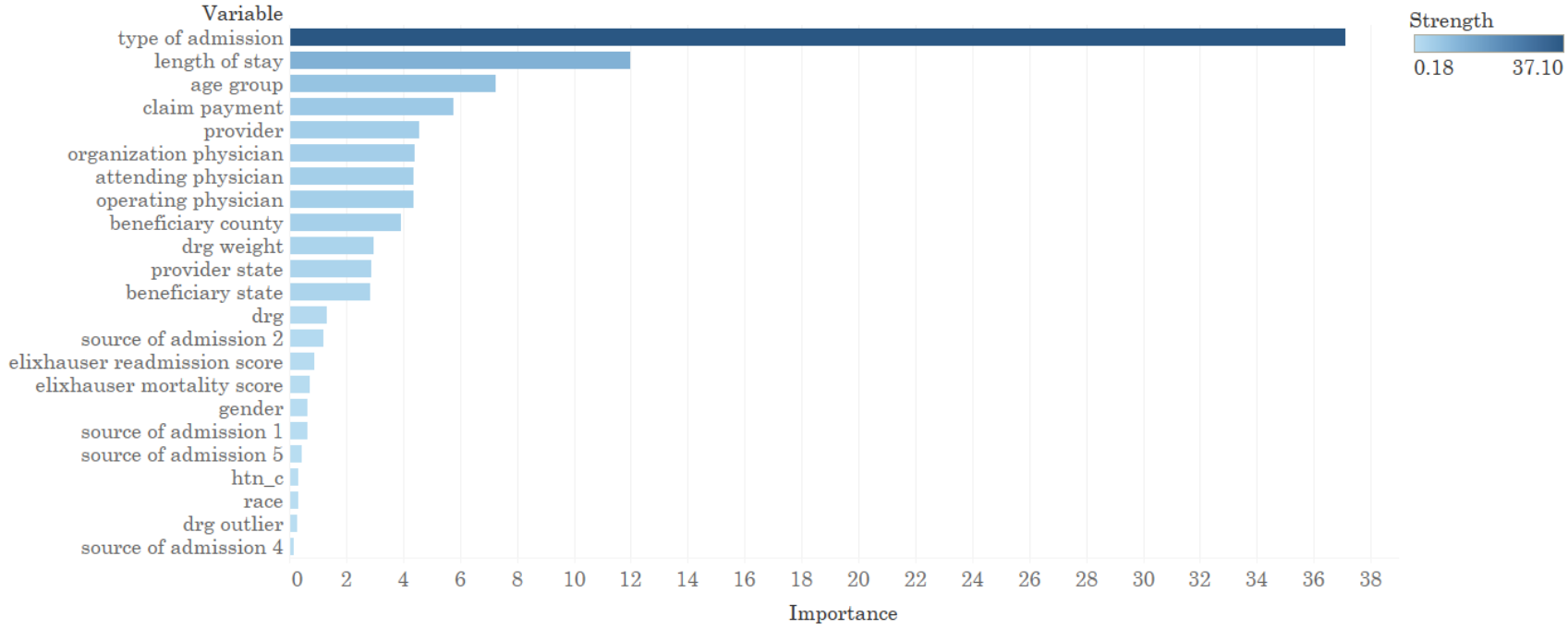



**Figure 23.** Predictors Most Involved in Random Forest Algorithm

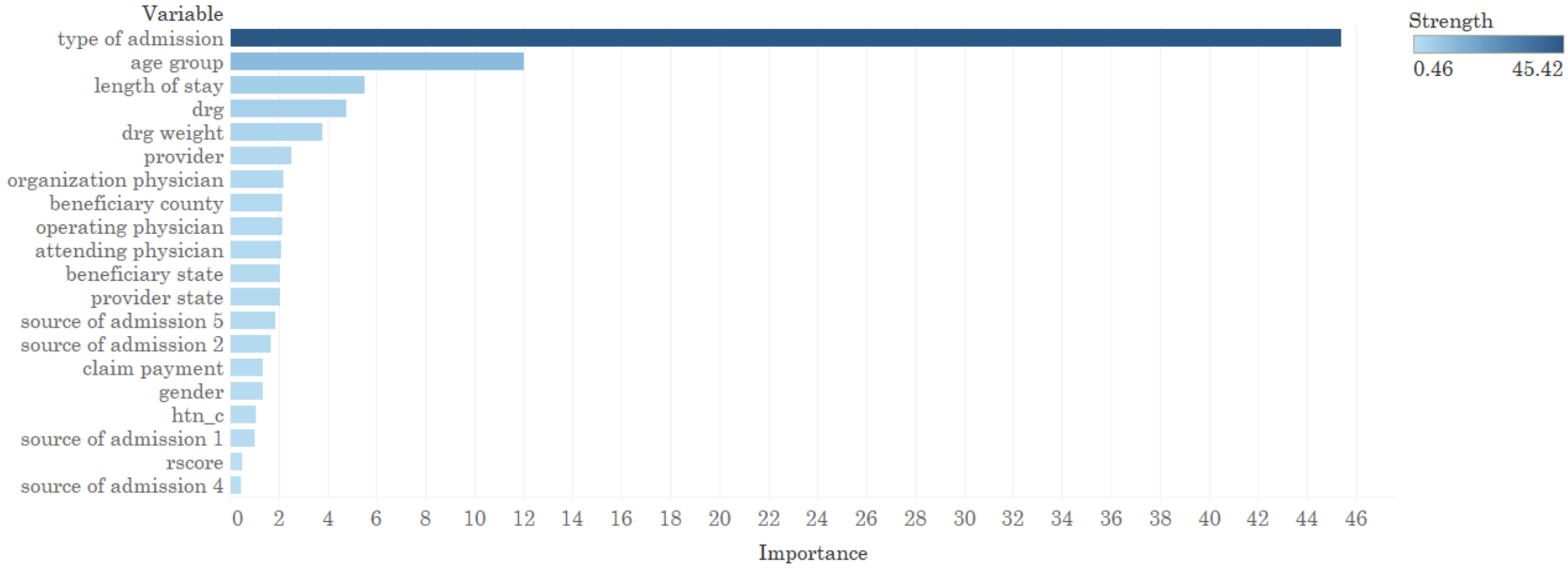



**Figure 24.** Predictors Most Involved in Extra Trees Algorithm

## 4.7 Data Mining using SAS Enterprise Miner

SAS Enterprise Miner was used to run the Naïve Bayes algorithm, as the Naïve Bayes algorithm was not available in Matlab 2016b, nor was it available on the MLJAR platform. Table 25 contains the results of the Naïve Bayes algorithm along with its associated ROC, Stddev, Var, ASE, and MISC. The algorithm was used with its out-of-the-box settings, as seen in Table 26. The ROC came in at 0.77 on the training dataset and 0.77 on the test dataset for the novel risk dependent variable. Additionally, the 15 strongest predictors were captured for each algorithm and are displayed in Table 27; the predictors that were the most involved were attending physician, operating physician, and organization physician.

**Table 25.** SAS Enterprise Miner Classification Algorithm—Naïve Bayes (15-Fold)

| | ROC | Stddev | Var | ASE | MISC |
|---|---|---|---|---|---|
| Train | 0.77 | 0.035 899 | 0.001 288 | 0.160 785 | 0.132 275 |
| Test | 0.77 | 0.016 348 | 0.000 267 | 0.169 019 | 0.152 579 |

**Table 26.** Default Out-of-the-Box Settings

| Variables | |
|---|---|
| Network Model | Naïve Bayes |
| Automatic Model Selection | Yes |
| Prescreen Variables | Yes |
| Variable Selection | Yes |
| Independence Test Statistics | G-Square |
| Significance Level | 0.2 |
| Missing Interval Variable | Mean |
| Missing Class Variable | Mode |
| Number of Bins | 10 |
| Maximum Parents | 5 |
| Network Structure | Parent-Child |
| Parenting Method | Set of Parents |

**Table 27.** Variable Ranking—Naïve Bayes

| Variable | Order | Score |
|---|---|---|
| attending physician | 1 | -7779.895 764 |
| operating physician | 2 | -7627.608 804 |
| organization physician | 3 | -5006.158 238 |
| provider | 4 | -1992.431 749 |
| beneficiary county | 5 | -1366.125 044 |
| provider state | 6 | -943.282 238 3 |
| beneficiary state | 7 | -940.162 881 8 |
| elixhauser readmission score | 8 | -804.119 376 8 |
| elixhauser mortality score | 9 | -803.299 706 2 |
| claim payment | 10 | -797.304 263 5 |
| source of admission | 11 | -779.504 743 2 |
| gender | 12 | -775.272 086 2 |
| race | 13 | -758.487 536 |
| age group | 14 | -720.324 69 |
| length of stay | 15 | -712.405 295 5 |

## 4.8 Model Validation

Regarding model validation of the inpatient claims test dataset for over fitting, under fitting, and performance, 15-fold cross validation and tuning of the models was implemented where available. All models were checked for high bias / low variance or low bias / high variance, and model complexity was considered in light of the sample size. Matlab's Neighborhood Component Analysis (NCA) was run against the training dataset. Claim payment, beneficiary county, operating physician, type of admission, elixhauser readmission score, and beneficiary state (in that order) were the result of NCA. Lastly, over fitting through model memorization was also considered due to the fact that on occasion the same beneficiary appeared in both the training and test dataset but under different claim numbers. The models used on the training dataset may capture the similarities of the beneficiary

observation in its algorithm. When used on a subsequent training, holdout or new data may cause inaccurate results. It is inconclusive, however, whether this effect occurred in this study.

Matlab's ensemble boosted tree algorithm performed the best across both the training and test dataset with the lowest average squared error. The inpatient claims data is highly unbalanced, with more majority class responses (1) than minority class responses (0). Matlab's ensemble RUSBoosted trees uses random under sampling with replacement to balance the majority and minority samples for higher accuracy in predictions. RUSBoosted trees performed equally as well when comparing ROC and had a slightly higher ASE. The novel risk response variable is a binomial class. Table 28 calculated the proportion for novel risk = 0 proportion was 0.1126, ASE 0.0012, at 95% confidence limits. The one-sided p-value supports the alternate hypothesis that the proportion of novel risk = 0 is less than 50%.

**Table 28.** Binomial Proportion for novelrisk=0

| novelrisk | Frequency | Percent |
|---|---|---|
| 0 | 8357 | 11.26 |
| 1 | 65 830 | 88.74 |

| Binomial Proportion | |
|---|---|
| novelrisk = 0 | |
| Proportion | 0.1126 |
| ASE | 0.0012 |
| 95% Lower Conf Limit | 0.1104 |
| 95% Upper Conf Limit | 0.1149 |
| | |
| Exact Conf Limits | |
| 95% Lower Conf Limit | 0.1104 |
| 95% Upper Conf Limit | 0.1149 |

**Table 28.** Continued

| Test of H0: Proportion = 0.5 | |
|---|---|
| ASE under H0 | 0.0018 |
| Z | -211.0085 |
| One-sided Pr < Z | <.0001 |
| Two-sided Pr >\|Z\| | <.0001 |

Sample Size = 74 187

## 4.9 Model Evaluation

While this is not a comprehensive review of every model used in the study. It provides a window into some of the performance difference across the MLjar, SAS Enterprise Miner, and Matlab models. MLjar algorithms were OOB and incapable of being tuned. All the MLjar algorithms were tree-based and preprocessing took place in the data's categorical values using one-hot encoding. Notable MLjar algorithm learning parameters were (1) time constraint for 5 minutes and (2) maximum steps at 500.

As detailed in Table 24, Tree settings for MLjar LightGBM were 250 for trees/iterations and 64 for number of leaves. Extreme Gradient Boosting—better known as XGBoost—likewise had a higher tree/iteration setting of 150, while Regularized Greedy Forest's tree/iteration setting was 950. MLjar's Random Forest tree/iteration setting was 115, its leaf setting was 17, and its split setting was 8 using the entropy criterion. MLjar Extra Trees settings were 20 for trees/iterations, 7 for number of leaves, and 15 for splits using the Gini Diversity Index. These settings are very different from the Matlab fine, medium, and coarse tree settings, which were considerably lower; however, all three recorded low ASE scores. Matlab SVM algorithms based on their ROC scores using a linear and gaussian kernel did not appear to separate the novel risk response variable cleanly by the hyperplane

created in the algorithm. Matlab Coarse KNN algorithm did perform well on both the training and test dataset, recording an ASE of 0.1011. Matlab Linear Discriminant algorithm builds a linear relationship from the independent variables to the dependent variable. SAS EM Naïve Bayes algorithm used a parent-child network structure and G-square for independence testing.

In summary all the algorithms' performances could benefit from further tuning and varied sample size through trial and error.

# CHAPTER V

# DISCUSSION

## 5.1 Discussion

This research was an exploration into the data mining of inpatient claims to identify viable independent variables as candidates for predictors of risk in the selected model. The aim was to predict a novel risk category dependent variable (binary) that was derived from emergency department visits, readmissions, and mortality variables in the sample. It was already understood through prior statistical modeling and literature that emergency department visits, readmission, and mortality were indicators of risk in MJR or reattachment of the lower extremity. The objective, therefore, was to use areas of cost, access, and quality in an inpatient beneficiary claim record as the starting place for data mining and excavation of independent variables and their associations with the binary dependent variable. Several MLJAR algorithms were able to generate ROC's of 0.80. Likewise, several Matlab algorithms generated ROC's of 0.80. SAS Enterprise Miner HP BN Classifier using a Naïve Bayes network model recorded a ROC of 0.77. Matlab's Ensemble Boosted Tree yielded the most reliable ROC results across both the training and test datasets – 0.80 and 0.81. Furthermore, its average square error was amongst the lowest showing it would be the most portable to other dataset delivering low variance and low bias.

White females made up over 60% of observations along with white female and males having the costliest claim payments. This points to McConnell et al[13] discussion regarding racial disparity in lower extremity joint replacement and Ibrahim et al[14] findings that blacks far more than white patients choose not to have major joint replacement of the lower extremity—specifically TKA. Further disparity is clearly seen in Figure 25 where the overwhelming number of claims with questionable risk belong to whites. Florida had the most claims with questionable risk, followed by California, then Texas. The latest United States census data[101] shows whites making up 76.6% of the population. In this study, whites made up 89.68% of the claims, approximately 13% more than the population value. While blacks census data[101] shows blacks making up 13.3% of the population, they only represented 6.11% of the claims. Other races show the same disparity between census population data and claims in this study. Obesity and hypertension (complicated & uncomplicated) were the most frequent comorbidities.

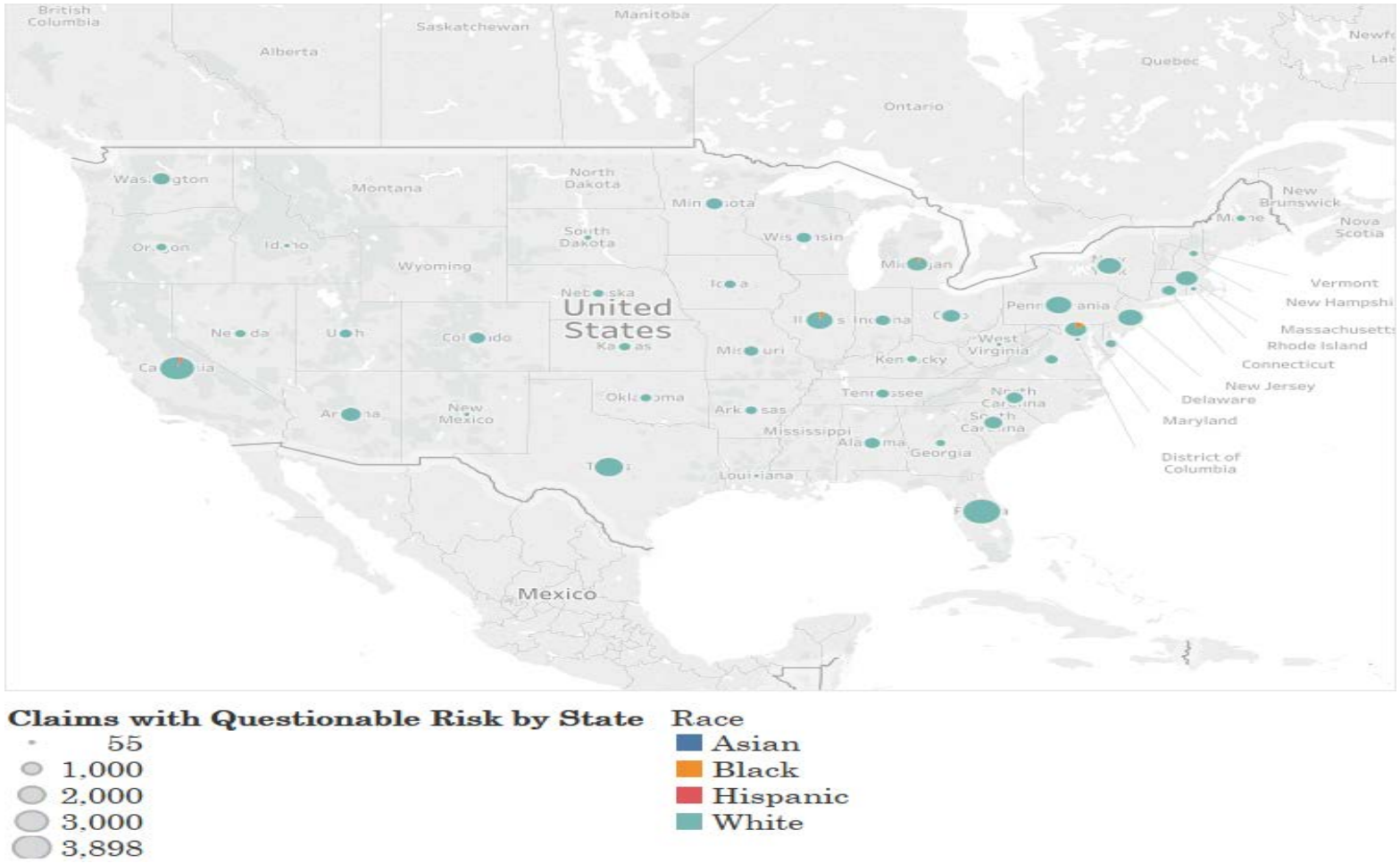
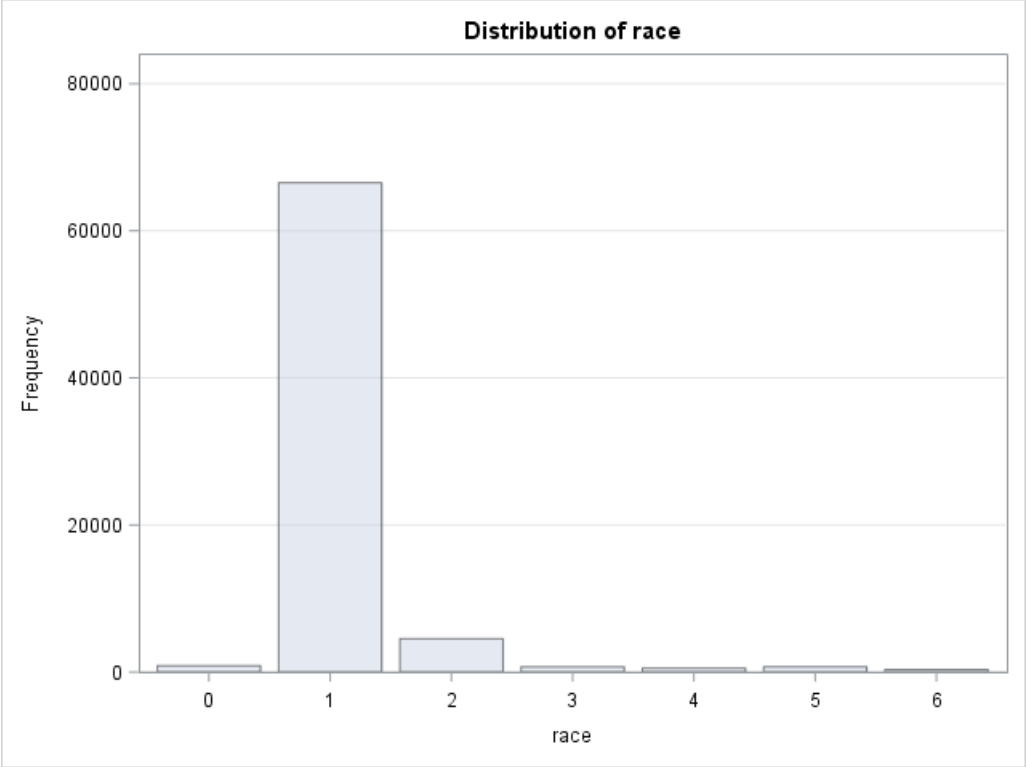
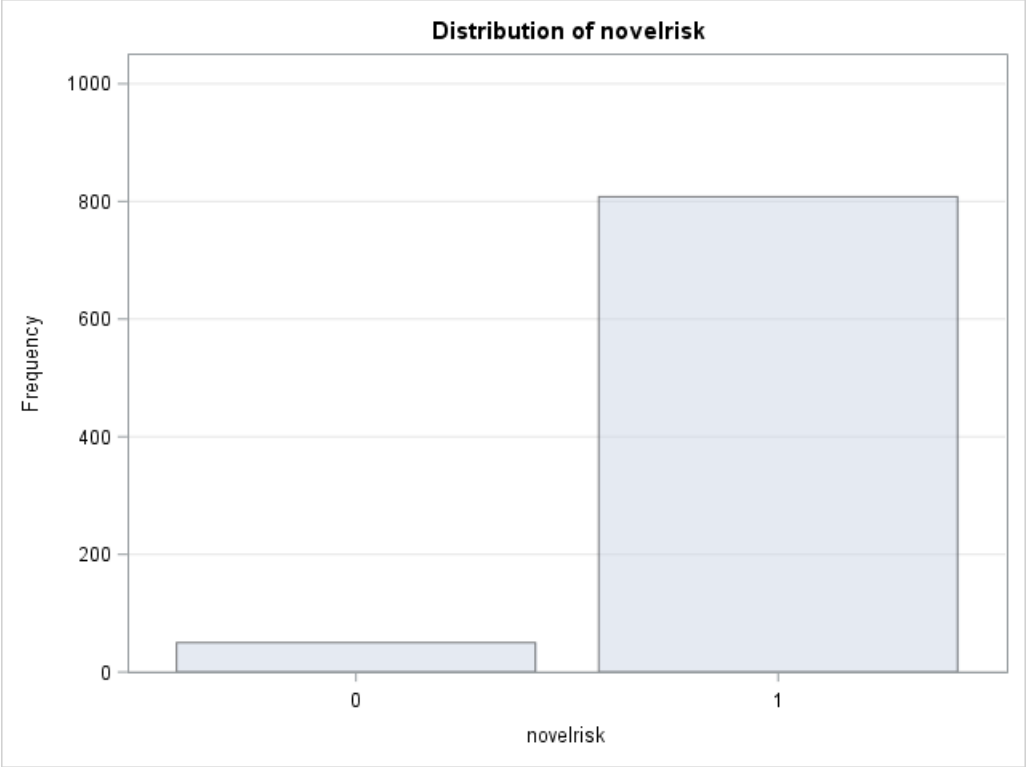



**Figure 25.** Claims with Questionable Risk by State & Race




| race | Frequency | Percent |
|---|---|---|
| 0-Unknown | 858 | 1.16 |
| 1-White | 66 531 | 89.68 |
| 2-Black | 4533 | 6.11 |
| 3-Other | 705 | 0.95 |
| 4-Asian | 519 | 0.70 |
| 5-Hispanic | 714 | 0.96 |
| 6-North American Native | 327 | 0.44 |

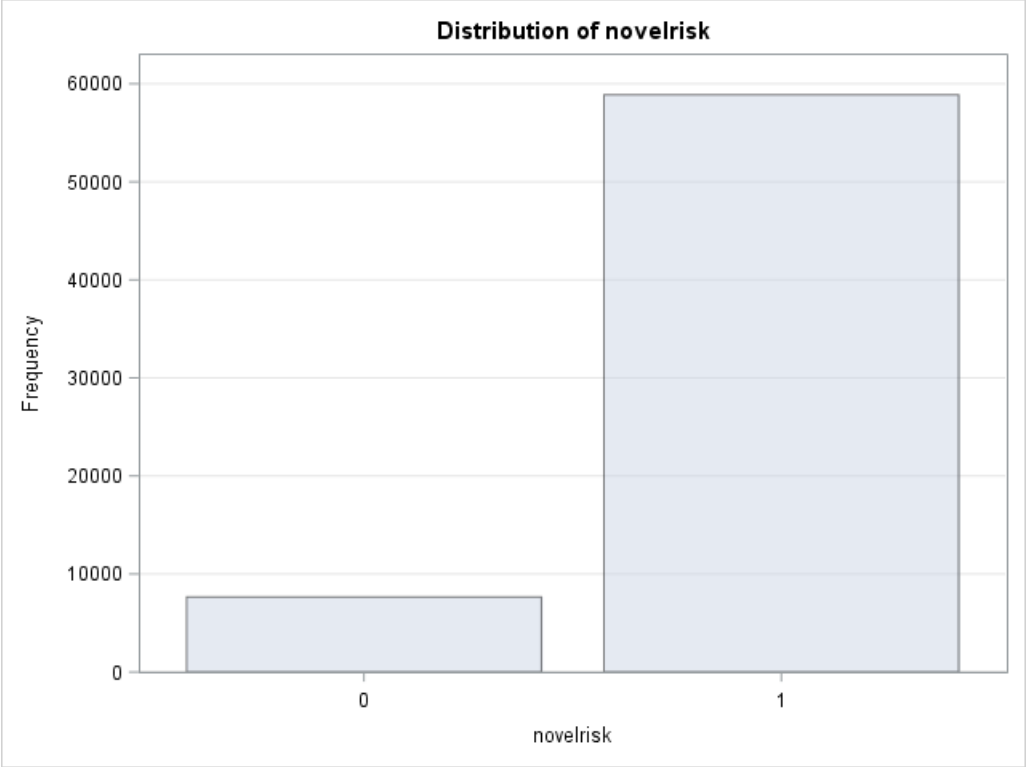
**Figure 26.** Distribution of Race




race=Unknown

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 50 | 5.83 |
| 1-Acceptable Risk | 808 | 94.17 |

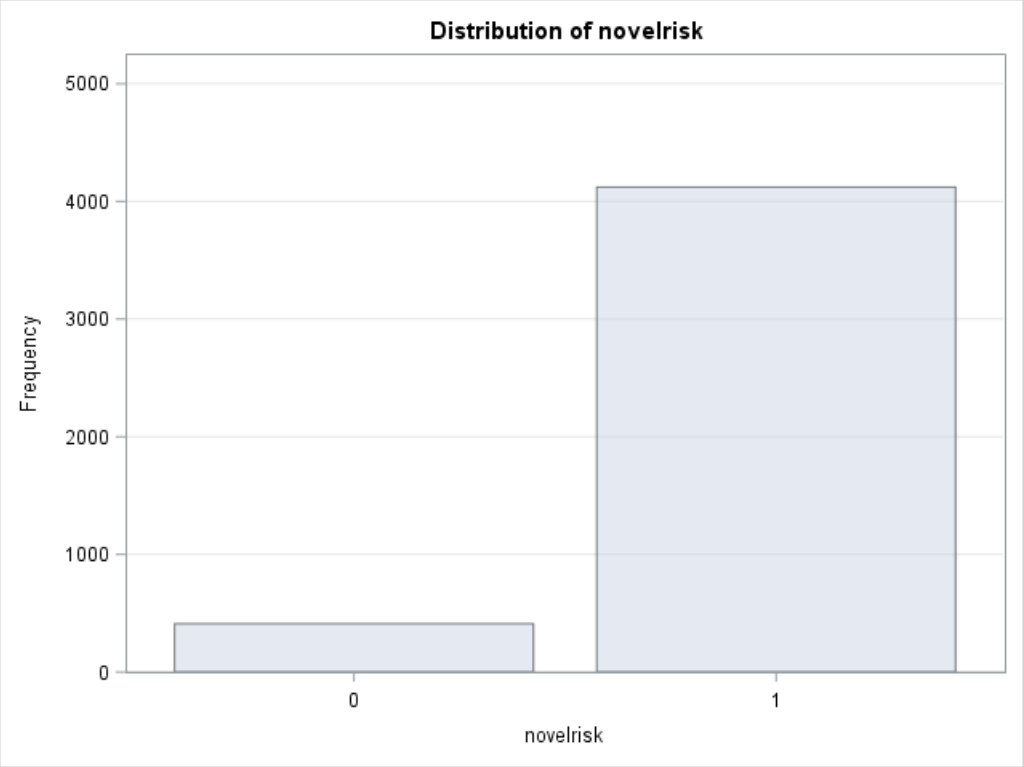
**Figure 27.** Distribution of Novel Risk for race=unknown




race=White

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 7657 | 11.51 |
| 1-Acceptable Risk | 58 874 | 88.49 |

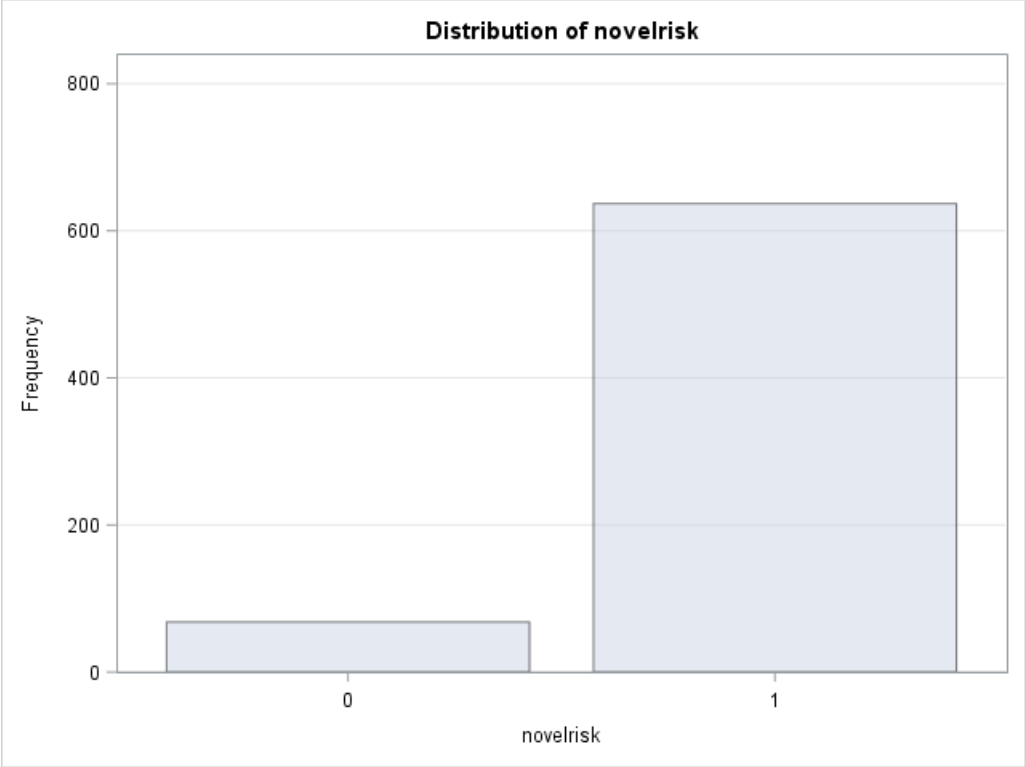
**Figure 28.** Distribution of Novel Risk for race=White




race=Black

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 411 | 9.07 |
| 1-Acceptable Risk | 4122 | 90.93 |

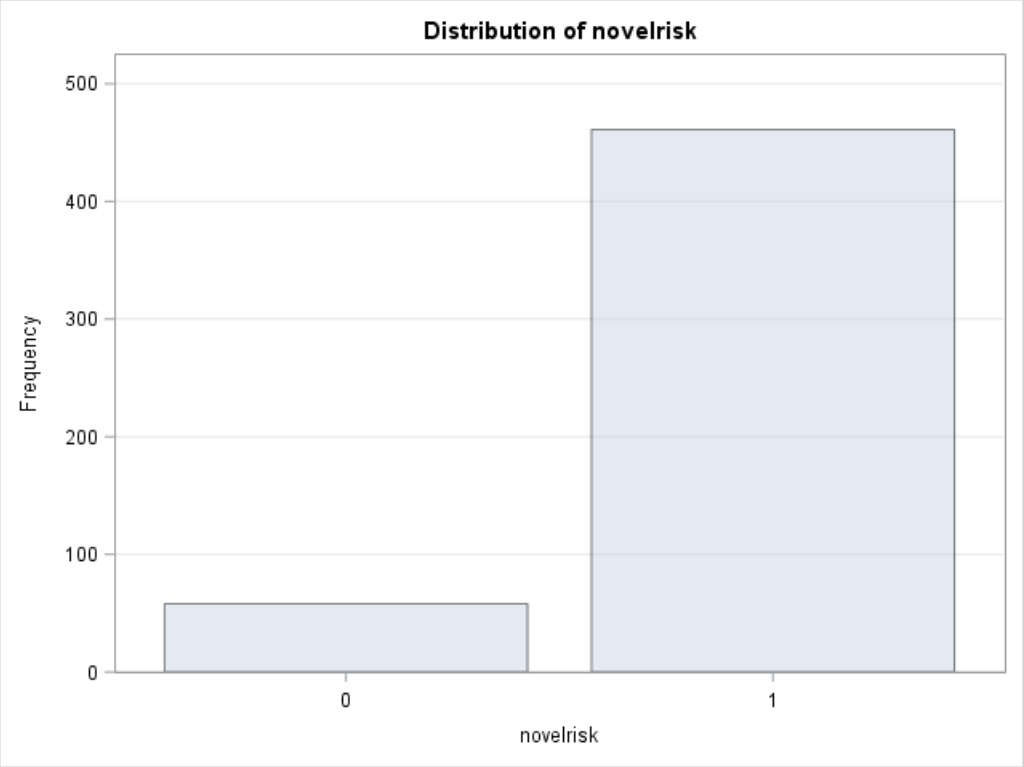
**Figure 29.** Distribution of Novel Risk for race=Black




race=Other

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 68 | 9.65 |
| 1-Acceptable Risk | 637 | 90.35 |

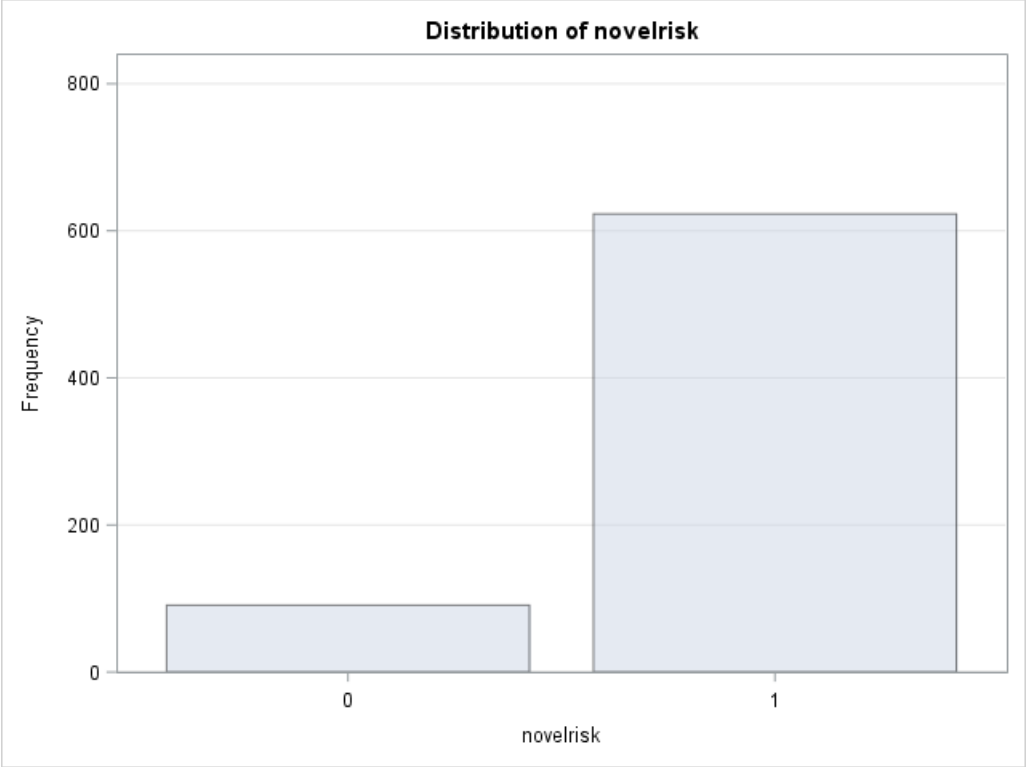
**Figure 30.** Distribution of Novel Risk for race=Other




race=Asian

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 58 | 11.18 |
| 1-Acceptable Risk | 461 | 88.82 |

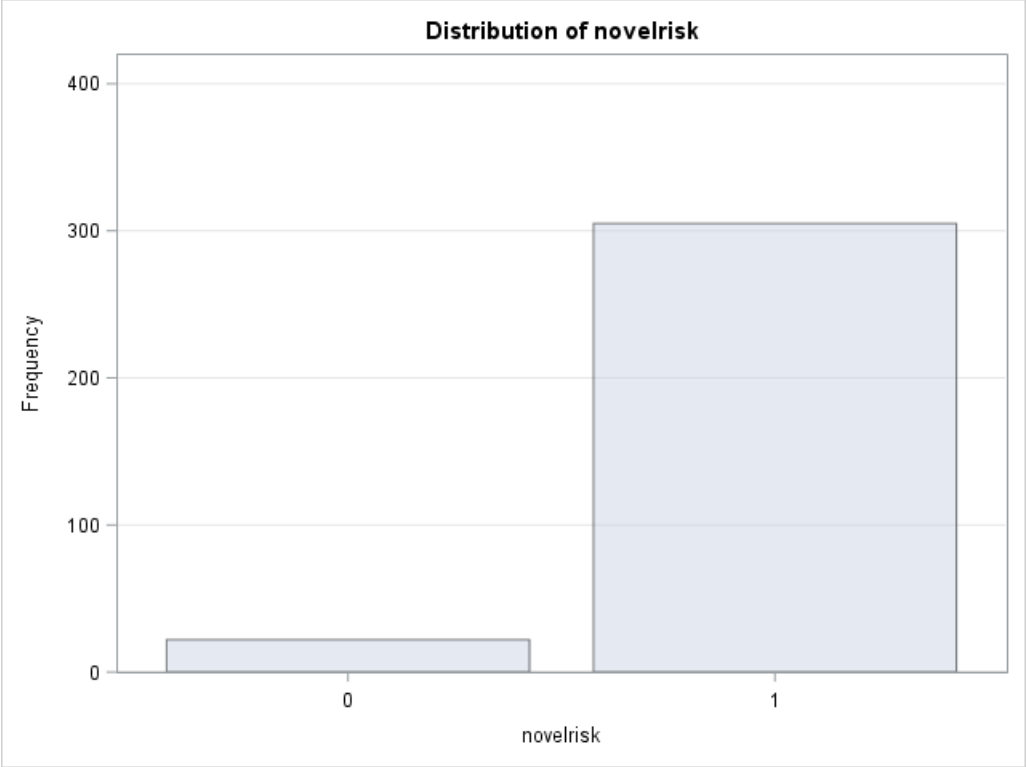
**Figure 31.** Distribution of Novel Risk for race=Asian




race=Hispanic

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 91 | 12.75 |
| 1-Acceptable Risk | 623 | 87.25 |

**Figure 32.** Distribution of Novel Risk for race=Hispanic




race=North American Native

| novelrisk | Frequency | Percent |
|---|---|---|
| 0-Questionable Risk | 22 | 6.73 |
| 1-Acceptable Risk | 305 | 93.27 |

**Figure 33.** Distribution of Novel Risk for race=North American Native

## 5.2 Significance of the Findings

The predictors that were most important in the MLJAR and SAS Enterprise Miner models consistently were claim payment, attending physician, operating physician, organization physician, provider, type of admission, and beneficiary county. This finding is significant not only for its ability to predict the novel risk flag; its true significance is that these predictors indicate that the physicians, the acute hospital (provider), and the beneficiary's county register a strong association to emergency department visits, readmission, and even mortality. While Matlab NCA returned claim payment as the strongest influencer on the response variable of novel risk, followed by beneficiary county, Matlab tree and ensemble algorithms returned type of admission as the strongest influencer. It can be inferred that any algorithm within Matlab using a tree structure would have tree weights. These predictors affect all three areas of the Iron Triangle: cost, access, and quality. Notably, however, the majority of the predictors were notated under the Access area of excavation. This insight allows clinicians, case works, and clinical informaticists to adjust and calibrate their risk-based models, quality programs, and early warning and surveillance systems to take these predictors into account when surveying ways of lowering cost, enhancing access, and improving quality.

## 5.3 Claim Payment

Claim Payment turned in a strong showing as an influencer on the response variable novel risk. Navathe et al[29] demonstrated that payment type (e.g., bundled payment for major joint replacement or reattachment of lower extremity) lowered spending. Courtney et al[30] showed that patients who undergo major joint replacement or reattachment of lower extremity showed a direct correlation between

cost, LOS, and comorbidities. Concerning cost and readmissions, it found that cost savings were realized through reduced readmissions and shorter lengths of stay.[31] Bolz and Iorio[37,38] examined potential cost savings from the implementation of BPCI, resulting in a statistically significant savings.[37,38] Dummit et al[7] contributed proof that incentivizing payment based on maintaining or increasing quality per episode is a viable approach. Edwards et al[42] under BPCI saw a 14% reduction in cost per episode, an average decrease in LOS from 3.81 to 2.57 days, and a decrease in readmissions from 16% to 10%, for an overall decrease in cost of 23%.[42] Significant cost savings occur when anchor stay is reduced, and the discharge is to a patient's home rather than to a PAC facility. Further results found cost decreased by 14% for those episodes participating in the BPCI group, anchor stay cost increased $102 per episode, LOS decreased from 3.81 to 2.57 days, and readmissions decreased from 16% to 10%.[42] This study reaffirmed the notion that significant opportunities for improving outcomes and cost savings are realized by reducing LOS and discharging to home.[42] Contrary to the aforementioned literature is Sullivan et al,[47] who provided analysis of the BPCI initiative. Their findings demonstrated a decline in Medicare payments for lower extremity joint replacement episodes without a meaningful change in readmission rates and mortality. Claim payment can show a strong association with readmission, emergency department visits, and mortality. Improvements in these areas will certainly lower Medicare payment.

### 5.4 Physician Performance

Based on the predictor strength outcomes, physician performance presents an opportunity for performance improvement and an area for potential cost savings. However, given the nature of claims data many times not showing the true picture

of the episode—specifically, in this case, for physicians—caution should be used when building predictive models where the analysis is centered on the attending physician. Fontana[102] penned his and his colleagues' experience using Medicare inpatient claims data along with physician data to identify causes of physician attribution errors, as presented in Table 29.

**Table 29.** Four indicators of potential physician attribution errors

| Attribution Flag | Definition |
|---|---|
| Over-responsible physician | A single physician is attributed to a far higher proportion of claims—5 or 10 times more—than physicians treating patients at the same organization |
| Emergency medicine physicians outside the ED | Emergency medicine physicians listed as attending on inpatient claims with a length of stay greater than two days |
| Non-physician as an attending | Non-physician (example, nurse, occupational therapist etc.) listed as attending physician |
| Anesthesiologist as attending for non-ICU cases | Anesthesiologist listed as attending in cases where more than 50% of the inpatient stay occurred outside of the ICU |

Source: Fontana[102]

## 5.5 Type of Admission

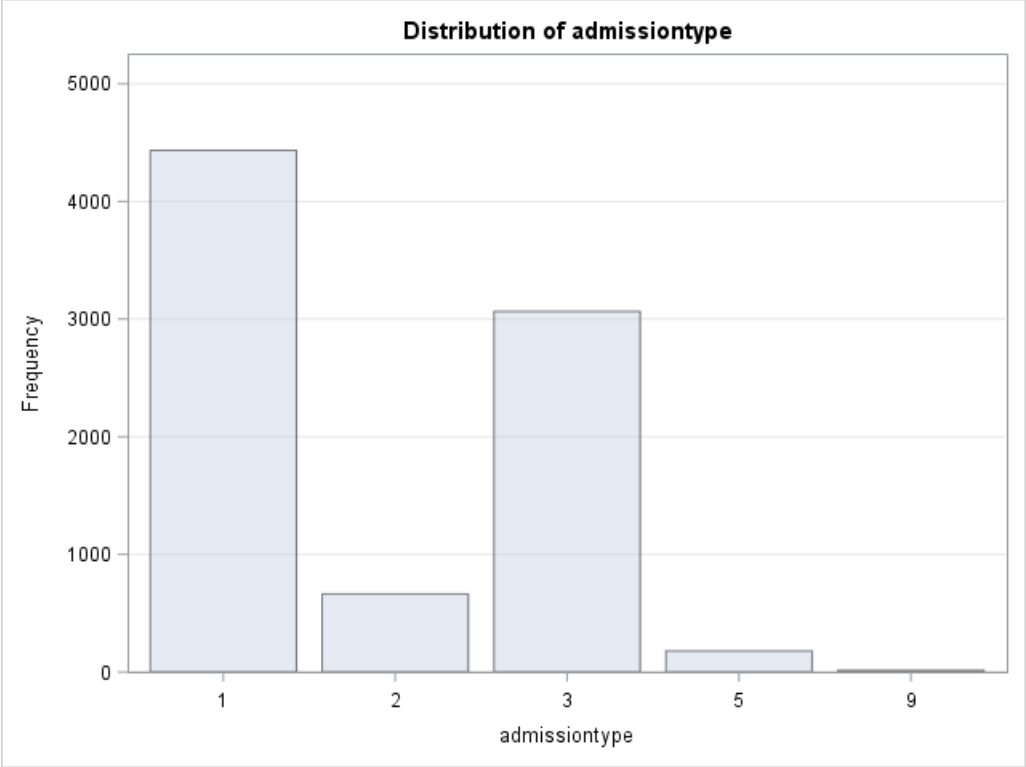
Type of Admission proved to be a strong influencer on the response variable novel risk. This variable described the admission and priority, as seen in Table 30. When querying ResDAC—the designated source for CMS data support regarding whether the Emergency code in Table 30 would include emergency department visits—there was no clear answer, as an emergency code can be coded on transfers from one hospital to another. Consider this example: Patient X has a heart attack and is admitted into Hospital A. Hospital A does not have a cardiac unit. Patient X is then transferred directly to Hospital B's cardiac unit for a higher level of acuity. This patient could be coded as an Emergency during the admittance on the inpatient

claim record. Or consider this case: Patient Y checks into Hospital A for an Outpatient procedure. During recovery from the procedure, Patient Y has a reaction to medication and is admitted into Hospital A as an Emergency. The coding of inpatient claims in this study for Type of Admission are shown by novel risk in Figures 34 and 35.

**Table 30.** Claim Inpatient Admission Type Code (FFS)

| Code | Code Value |
|---|---|
| 0 | Blank |
| 1 | Emergency – The patient required immediate medical intervention as a result of severe, life threatening, or potentially disabling conditions. Generally, the patient was admitted through the emergency room. |
| 2 | Urgent – The patient required immediate attention for the care and treatment of a physical or mental disorder. Generally, the patient was admitted to the first available and suitable accommodation. |
| 3 | Elective – The patient's condition permitted adequate time to schedule the availability of suitable accommodations. |
| 4 | Newborn – Necessitates the use of special source of admission codes. |
| 5 | Trauma Center – visits to a trauma center/hospital as licensed or designated by the State or local government authority authorized to do so, or as verified by the American College of Surgeons and involving a trauma activation. |
| 6–8 | Reserved |
| 9 | Unknown – Information not available. |

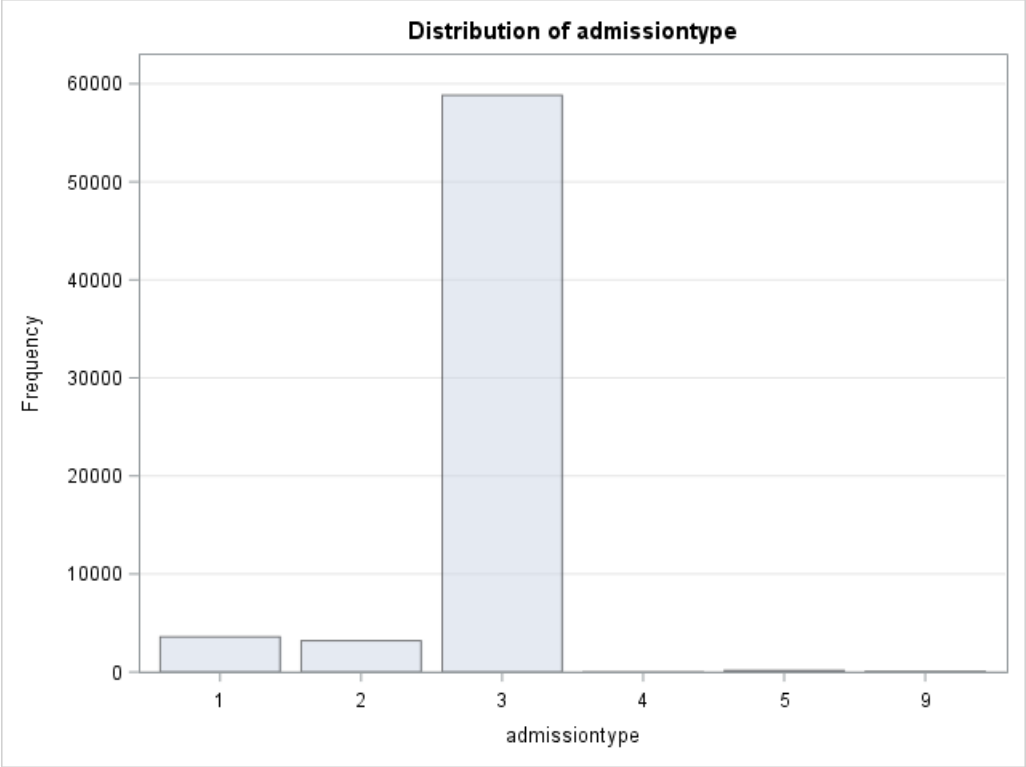
Source: ResDAC[103]




novelrisk=0

| Admission type | Frequency | Percent |
|---|---|---|
| 1-Emergency | 4434 | 53.06 |
| 2-Urgent | 664 | 7.95 |
| 3-Elective | 3065 | 36.68 |
| 5-Trauma Center | 179 | 2.14 |
| 9-Unknown | 15 | 0.18 |

**Figure 34.** Results for Type of Admission for novelrisk=0




novelrisk=1

| Admission type | Frequency | Percent |
|---|---|---|
| 1-Emergency | 3587 | 5.45 |
| 2-Urgent | 3195 | 4.85 |
| 3-Elective | 58 829 | 89.37 |
| 4-Newborn | 1 | 0.00 |
| 5-Trauma Center | 158 | 0.24 |
| 9-Unknown | 60 | 0.09 |

**Figure 35.** Results for Type of Admission for novelrisk=1

## 5.6 How These Findings Relate to What Others Have Done

At the end of 2018, Navarro et al[10] and Ramkumar et al[11] both published their findings using a similar research design on inpatient data from Medicare plans for TKA and THA patients, respectively. The experiment data for TKA was mined using a machine learning Bayesian Network model that also recorded an ROC of 0.8669; for THA, an ROC of 0.7822 was recorded. Notable to the research conducted in this study, like Navarro et al[10] and Ramkumar et al,[11] this study used claims data and a comorbidity index on lower extremity joint replacements.

## 5.7 Limitations of the Findings

The findings were primarily based on the limitations in the Inpatient Limited Datasets used in this research. The data by its very nature and namesake is a limited dataset. There are columns of data that are not available in the LDS files. Also, the level of detail in some cases is not available or grouped into ranges. LDS files do not contain protected health information (PHI), nor does access to the datasets require a privacy review by CMS. Furthermore, models run on the SAS EM platform were run without vigorous modification to model specific parameters and tuning. MATLAB models were run using the Classification Learner applications setting out-of-the-box. As mentioned previously, beneficiaries had multiple claims. However, each claim number is unique. Limits in CMS administrative data in research are listed in Table 31.

**Table 31.** Strengths and Limitations of CMS Administrative Data in Research

| | |
|---|---|
| Record of Care Received | Conditions must be diagnosed in order to appear in the utilization files; however, some diseases such as hypertension, depression and diabetes are often under-diagnosed. In addition, while the files provide a reliable record of the care received by the beneficiary, they do not provide information on the care *needed*. It is difficult to study disease recurrence in detail since all the data may reveal is the start of a new treatment.<br><br>Another important point is that services that providers know in advance will be denied may be inconsistently submitted as bills and, therefore, inconsistently recorded in the files. |
| Diagnosis Information | Diagnosis information may not be comprehensive enough in some cases to allow detailed analysis. For example, a cancer diagnosis can be found as an ICD-9 diagnosis code in the data (e.g. lung cancer is 162.xx), but no information on stage or histology is included in the Medicare claims data.<br>The data do contain information on chronic diseases; however, knowing that someone has a chronic disease does not reveal how long they have had the condition (incidence vs. prevalence) or the severity of their condition. |
| Inconsistencies in Use of Coding Systems for Procedures by Care Setting | Different care settings use different coding systems for procedures treated in inpatient and outpatient settings. For example, inpatient care is coded using ICD-9 procedure codes (4 digits), while physician/supplier and durable medical equipment data are coded using CPT and HCPCS codes. Furthermore, hospital outpatient care is coded as a mix of CPT and revenue center (hospital billing center) codes. Currently, there exists a less-than-perfect crosswalk between ICD-9 codes and CPT codes. |
| Limited Clinical Information | Physiological measurements such as blood pressure, pulse, and cardiac ejection fraction are absent from the utilization files. In addition, results of common tests such as PSA, angiography and pathological tests are not included. Exact timing of events can be difficult to discern. Specifically, the time from admission to a given |

| | |
|---|---|
| | event or timestamps for dates of service cannot be found in the data. |
| Exclusions in Utilization Data | Outlined below are several types of services and care that are not contained in the Medicare data.<br>2) Covered services for which claims are not submitted are not included in the data (e.g. immunizations provided through grocery-store immunization clinics).<br>3) Some services are not covered by Medicare and would, therefore, not be included. |
| Variable Quality | A good rule of thumb when trying to determine the reliability of a given data field is this: If the information impacts payment, then the quality of that information will be better. Keeping this in mind, different types of care may be subject to different payment rules. This implies that, for example, comorbidity and severity of illness information may be inconsistently recorded if they are subject to varying payment rules. In addition, some components of treatments may not be included in bills (and therefore in the claims data) if reimbursement rates are very low, even if the treatment is provided. |

Source: Vernig and Parsons[104]

## 5.8 Surprising, Unexpected, or Inconclusive Results

Surprisingly, the Elixhauser Comorbidity Index scores for readmission and mortality did not play a significant role as important variables in any of the model experiments. Inconclusive results were received running the SAS EM algorithms; their receiver operating curves either overfit or underfit the data. Unfortunately, these models and their results were unreportable and eliminated from this study.

## 5.9 Suggestions for further research

Further research is recommended with the following caveats:

- Use the Research Identifiable Files rather than the Limited Data Set files.
- Include the following files in the research: outpatient, SNF, Home Health, Carrier, and Durable medical equipment regional carrier, allowing for the reconstruction of episodes.
- Take the time to dive deep into understanding the central tendencies of all variables.
- Fully investigate all the parameters and hyper-tuning features applicable to each machine learning algorithm.
- Consider binning and feature dimensionality reduction.

# CHAPTER VI

# SUMMARY AND CONCLUSION

## 6.1 Summary

This study started with the notion that the healthcare system in America needs an overhaul and that one area that could benefit immensely is MJR. The Iron Triangle (cost, access, and quality) was chosen as the overarching framework that improvements would be viewed through. Statistical and supervised machine learning algorithms were analyzed for their ability to predict a novel risk flag created in each beneficiary claim record that considered emergency department visits, readmissions, and mortality as known indicators of risk in an inpatient stay for MJR. Three data mining platforms were used with a diverse suite of machine learning algorithms to mine 74 187 nationwide Medicare inpatient beneficiary claims. The models created from the algorithms were compared to each other, and model selection was based on the result with the highest ROC across training and test datasets with the lowest ASE. After selection, the model's predictors were reviewed to determine strength of their role in creating the model. The experiments in the study concluded that the Ensemble Boosted Tree performed the best across both training and test dataset. The outcomes of these machine learning models were better than the statistical modeling conducted with binary logistic regression.

Social determinants of major joint replacement or reattachment of the lower extremity were not fully investigated in this study except for age group, gender, and race. Data mining social determinants such as education level, physical activity level, behavioral factors, socioeconomic factors, psychosocial factors, biological factors, etc. could potentially yield other influential predictors. Another trend is patients traveling to a center of excellence for TJA. Nwachukwu et al[105] investigated whether there was an association between the risk of a complication due to distance traveled by the patient, and their findings indicated no association. One of the goals of the centers of excellence is to develop best practices in TJA and provide the highest quality, thus distinguishing themselves as the national leader in TJA.[106]

The predictors that were strongly associated with the response variable novel risk were age group, attending physician, beneficiary county, beneficiary state, operating physician, organization physician, provider, type of admission, and provider state. These findings indicate that these predictors factor into emergency department visits, readmissions, or mortality at least 8 out of 10 times. At the onset of this research, the question was whether the independent variables (IV) are significantly associated with the dependent variable novel risk. Here at the conclusion, the results showed independent variable predictors played a significant role in determining the outcome of the novel risk when assessing the data.

This study contributes actionable findings for clinicians, healthcare administrators, informaticists, and researchers to build upon and investigate further. Furthermore, this research contributes knowledge and peer reviewed literature to filling and bridging the gap in research into major joint replacement or reattachment of lower extremity using machine learning algorithms.

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APPENDIX A

## SUPPLEMENTAL DATA

**Table 32.** Draft ICD-10-CM/PCS MS-DRGv28 Definitions Manual[4]

| Diseases & Disorders of the Musculoskeletal System & Connective Tissue<br>Major Joint Replacement or Reattachment of Lower Extremity |
|---|
| Replacement of Right Hip Joint |
| 1. with Autologous Tissue Substitute |
| 2. with Synthetic Substitute, Metal on Polyethylene |
| 3. with Synthetic Substitute, Metal on Metal |
| 4. with Synthetic Substitute, Ceramic on Ceramic |
| 5. with Synthetic Substitute, Ceramic on Polyethylene |
| 6. with Synthetic Substitute |
| 7. with Nonautologous Tissue Substitute |
| 8. Acetabular Surface with Autologous Tissue Substitute |
| 9. Acetabular Surface with Synthetic Substitute, Metal |
| 10. Acetabular Surface with Synthetic Substitute, Ceramic |
| 11. Acetabular Surface with Synthetic Substitute, Polyethylene |
| 12. Acetabular Surface with Synthetic Substitute |
| 13. Acetabular Surface with Nonautologous Tissue Substitute |
| Replacement of Left Hip Joint |
| 14. with Autologous Tissue Substitute |
| 15. with Synthetic Substitute, Metal on Polyethylene |
| 16. with Synthetic Substitute, Metal on Metal |
| 17. with Synthetic Substitute, Ceramic on Ceramic |
| 18. with Synthetic Substitute, Ceramic on Polyethylene |
| 19. with Synthetic Substitute |
| 20. with Nonautologous Tissue Substitute |
| Replacement of Right Knee Joint |
| 21. with Autologous Tissue Substitute |
| 22. with Synthetic Substitute |
| 23. with Nonautologous Tissue Substitute |

**Table 32.** Continued

| |
|---|
| Replacement of Left Knee Joint |
| 24. with Autologous Tissue Substitute |
| 25. with Synthetic Substitute |
| 26. with Nonautologous Tissue Substitute |
| Replacement of Left Hip Joint |
| 27. Acetabular Surface with Autologous Tissue Substitute |
| 28. Acetabular Surface with Synthetic Substitute, Metal |
| 29. Acetabular Surface with Synthetic Substitute, Ceramic |
| 30. Acetabular Surface with Synthetic Substitute, Polyethylene |
| 31. Acetabular Surface with Synthetic Substitute |
| 32. Acetabular Surface with Nonautologous Tissue Substitute |
| Replacement of Right Ankle Joint |
| 33. with Autologous Tissue Substitute |
| 34. with Synthetic Substitute |
| 35. with Nonautologous Tissue Substitute |
| Replacement of Left Ankle Joint |
| 36. with Autologous Tissue Substitute |
| 37. with Synthetic Substitute |
| 38. with Nonautologous Tissue Substitute |
| Replacement of Right Hip Joint |
| 39. Femoral Surface with Autologous Tissue Substitute |
| 40. Femoral Surface with Synthetic Substitute, Metal |
| 41. Femoral Surface with Synthetic Substitute, Ceramic |
| 42. Femoral Surface with Synthetic Substitute |
| 43. Femoral Surface with Nonautologous Tissue Substitute |
| Replacement of Left Hip Joint |
| 44. Femoral Surface with Autologous Tissue Substitute |
| 45. Femoral Surface with Synthetic Substitute, Metal |
| 46. Femoral Surface with Synthetic Substitute, Ceramic |
| 47. Femoral Surface with Synthetic Substitute |
| 48. Femoral Surface with Nonautologous Tissue Substitute |
| Replacement of Right Knee Joint |
| 49. Femoral Surface with Autologous Tissue Substitute |
| 50. Femoral Surface with Synthetic Substitute |
| 51. Femoral Surface with Nonautologous Tissue Substitute |

**Table 32.** Continued

| |
|---|
| Replacement of Right Knee Joint |
| 52. Femoral Surface with Autologous Tissue Substitute |
| 53. Femoral Surface with Synthetic Substitute |
| 54. Femoral Surface with Nonautologous Tissue Substitute |
| Replacement of Right Knee Joint |
| 55. Tibial Surface with Autologous Tissue Substitute |
| 56. Tibial Surface with Synthetic Substitute |
| 57. Tibial Surface with Nonautologous Tissue Substitute |
| Replacement of Left Knee Joint |
| 58. Tibial Surface with Autologous Tissue Substitute |
| 59. Tibial Surface with Synthetic Substitute |
| 60. Tibial Surface with Nonautologous Tissue Substitute |
| Supplement Right Hip Joint |
| 61. with Resurfacing Device |
| 62. Acetabular Surface with Resurfacing Device |
| Supplement Left Hip Joint |
| 63. with Resurfacing Device |
| 64. Acetabular Surface with Resurfacing Device |
| Supplement Hip Joint, Femoral Surface with Resurfacing Device |
| 65. Right |
| 66. Left |
| Reattachment of Femoral Region |
| 67. Right |
| 68. Left |
| Reattachment of Upper Leg |
| 69. Right |
| 70. Left |
| Reattachment of Knee Region |
| 71. Right |
| 72. Left |
| Reattachment of Lower Leg |
| 73. Right |
| 74. Left |

**Table 32.** Continued

| |
|---|
| Reattachment of Ankle Region |
| 75. Right |
| 76. Left |
| Reattachment of Foot |
| 77. Right |
| 78. Left |