EVALUATING INCREASING HOSPITAL CLOSURE RATES IN U.S: A MODEL FRAMEWORK AND A LEAN SIX SIGMA DEPLOYMENT APPROACH FOR QUALITY IMPROVEMENT INITIATIVES TO PREVENT FURTHER CLOSURES IN RURAL AND DISADVANAGED LOCATIONS

by

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ABSTRACT

EVALUATING INCREASING HOSPITAL CLOSURES RATES IN U.S: A MODEL FRAMEWORK AND A LEAN SIX SIGMA DEPLOYMENT APPROACH FOR QUALITY IMPROVEMENT INITIATIVES TO PREVENT FURTHER CLOSURES IN RURAL AND DISADVANAGED LOCATIONS

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Hospital Closures occur from time to time. Several rural hospitals were closed in the U.S recently in an unprecedented manner and hundreds of others are at the risk of closing. The Patient Protection and Affordable Care Act (PPACA) which was amended in 2010, has brought sea of changes in the healthcare industry right from changing the way how hospitals receive reimbursements by introducing several new programs targeting hospitals' quality of care to expanding health insurance for millions of poor and underprivileged populations in the country.

The goal of this study is to understand the closure of rural hospitals in line with the recent reform changes and identifying counter measures to prevent further closures in the future.

The first section of the research identifies and evaluates the factors behind the closures by creating a binary logistic model to predict closures of hospitals. Three models were created, first using patient and market characteristics factors (Financial Importance), second using hospitals core measure processes (Operational Importance) and a final model combining the above both models.

The second section of the research identifies and evaluates process improvement initiatives by deploying Lean Six Sigma projects in the hospitals. A Hospital Enterprise System (HES) which encompass

three hospitals is used for the study. A 0-1 Integer Linear Programming method (Knapsack Method) is proposed for the selection of projects. Two scenarios are created in which the first scenario optimizes the cost savings by selecting projects among three hospitals. In the second scenario, one among the three hospitals are assumed to be present in a disadvantaged location and few core measure projects are mandatorily implemented to improve the performance of processes to avoid penalties, reimbursement cuts and achieve cost savings to prevent closures in the future.

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A

ACO-Accountable Care Organization

ACA- Affordable Care Act

AMI- Acute Myocardial Infarction

C

CHIP- Children's Medical Insurance Program

CMS-Centers for Medicare and Medicaid

COPD- Chronic Obstructive Pulmonary Disease

CAP- Community Acquired Pneumonia

CAH- Critical Access Hospitals

D

DRG- Diagnosis-Related Group

H

HCAHPS- The Hospital Consumer Assessment of Healthcare Providers and Systems

HES- Hospital Enterprise System

HVBP- Hospital Value Based Purchasing Program

HRRP- Hospital Readmissions Reduction Program

HAC- Hospital Acquired Condition Reduction Program

I

IQR- Hospital Inpatient Quality Reporting

M

MedPAC- Medicare Payment Advisory Commission

N
NRHA- National Rural Health Association

NPV- Net Present Value

P
Patient Protection and Affordable Care Act

T

TPS- Total Performance Score

Chapter 1

Introduction

1.1 Overview

The United States has witnessed huge reforms and changes in the Healthcare industry during recent times. The recent reform enacted in 2010 is believed to have changed the landscape of the healthcare system in the country. The federal government's initiatives to improve the current healthcare scenario in the country is reflected from the expansion of Medicaid, establishing Health Insurance Marketplaces, with the intention of expanding health insurance coverage for economically challenged and common man alike. Since then, a record number of people have been newly insured as the Medicaid program is intended to cover 17 million newly insured people (Reinberg). As of 2014, about 8.02 Million people enrolled through State exchanges and 5.02 Million people enrolled for Medicaid(Mangan). Other important changes contained within the reform includes the transition from traditional fee-for-service reimbursements to value based ones by targeting quality of hospital care. Several new programs such as the Hospital Readmission Reduction Program (HRRP), Hospital Value Based Purchasing program(HVBP), Hospital Acquired Condition Reduction Program (HAC) etc. were implemented to improve patient outcomes and reduce unnecessary healthcare costs by penalizing and reducing reimbursements for hospitals who do not perform on par with other good performing hospitals nationwide.

In sharp contrast to the above healthcare industry events, which tends to lead us to believe that the country's healthcare situation is on an upward improving trend, there are some serious issues and concerns that are simultaneously happening at present, which needs some immediate attention. One important formidable issue is the hospitals closures that are happening around the country, particularly in recent years. In a country where half the population are from rural areas, 79 rural hospitals have closed since 2010 and 673 hospitals are on the verge of closing (Daly).

1.2 Impacts of Rural Hospital Closures:

Although the number of hospitals closed so far appear small, closure of a hospital in rural area might have far more complications than we would expect. The number of hospitals serving a county or a town in rural areas are very low compared to urban areas. When a hospital halts its service, the patients, must travel very long distances to find the next closest hospital for care. The situation becomes even worse when the patient is in a medical emergency such as experiencing heart attack, stroke etc. reports have surfaced on the casualties of patients who lost their lives due to traveling long distances for treatment (Lieb, Walters). The problems do not stop here. Hospitals have been one of the major revenue yielding businesses in rural areas as they are often one of the biggest and highest-paying employers in those areas and when they close, they have a domino effect on the other local businesses (Walters). Hospitals of varying sizes and capabilities are being closed permanently or get converted to emergency and outpatient clinics. In some hospitals, its vital processes are temporarily affected disrupting the care for the patients.

1.3 Purpose of this Research

Hospital closures in many instances have been viewed in a perspective such that the associated factors that affect closures are present external to the hospital. This research incorporates and evaluates the factors that are present within the hospitals and that affect closures. It also focuses on hospital closures in disadvantaged locations and suggests ways to prevent closure problems in the future. Given the changes and decisions contained within PPACA to improve quality of care, such as transitioning from traditional fee-for service to value based reimbursements, it is more likely that the changes may have affected the rural hospitals, as even 3% of the reimbursement cut can translate in to hundreds of thousands of dollars and many hospitals operate on a negative operating margin (average operating margin for rural hospitals is -11%). In this situation, the hospitals are under tremendous scrutiny on the quality of care given to patients and increased pressure to improve their care processes for retaining complete reimbursements and avoiding penalties. Patients are enabled to make informed decisions about choosing care givers, thereby forcing the hospitals to make improvements in order to stay competitive and attract patients. Thus, it is imperative to understand the baseline status of rural hospitals on their performance levels and provide solutions to prevent further closures in the future. The second section of this research provides remedial strategies for hospitals by improving processes through the deployment of Lean Six Sigma. By implementing Lean Six Sigma, the cost savings achieved through improvements will help to alleviate the risks and prevent further closures in the future.

1.4 Research Objectives

The research objectives are divided in to three parts. The first objective is to identify the factors that are involved in recent closures and the second objective is to evaluate whether the factors may have contributed to the risk of closure. The third objective illustrates an action plan in the form of deploying Lean Six Sigma projects to avoid closure problems in the future. Each research objective is explained in detail here below.

1.4.1 Research Objective 1: Identify the Hospital Closure Risk Factors based on Financial and Operational Importance

Hospital closures occur regularly. Several factors play a role to bring a hospital's operations to a halt. But in recent years since 2010, the rate of rural hospital closures in the U.S has been steadily increasing until now. At the same time, the country's healthcare industry experienced several changes due to the healthcare reform act that was amended in 2010. Hence the first objective is to determine the causes behind the increasing rate of hospital closures in such a way to correlate with the reform changes. In addition, other potential closure factors are identified for evaluation. In this part of the research, factors are classified in to two categories namely financial importance and operational importance factors. Factors that are external to the hospital that may contribute to the risk of closure are named as financial factors and factors that are internal to the hospital (i.e., factors that are responsible by the hospital are named as operational factors).

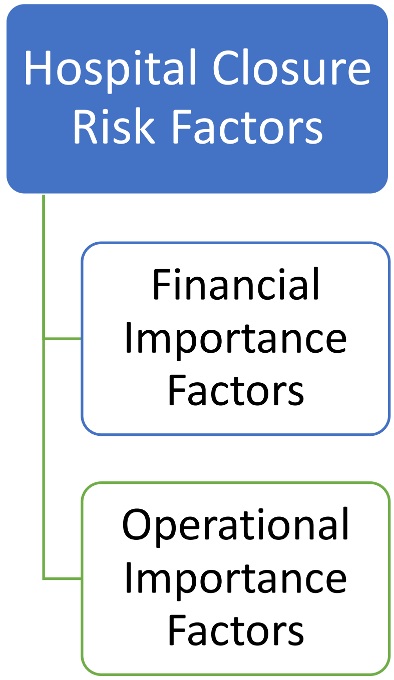


Figure 1.1: Hospital Closure Risk Factors Classification

1.4.2 Research Objective 2: Evaluate the Hospital closure risk factors to determine the likelihood of causing the risk of closure

In research objective 2, the factors identified in the previous research objective are evaluated by creating a predictive model using statistical methods to see if they cause the risk of hospital closures. The factors are evaluated individually based on operational importance model, financial importance model and finally as a combined importance model of both.

The gains attained from this component of the research is a model that the hospitals can use to evaluate themselves against their performances on certain core measures which can potentially contribute to the risk of closures. By knowing their standing on the performances, it will help hospital administrators to make quick decisions and plans to improve their performance levels in an effort to alleviate the risks. The model will also influence state officials to make changes to policy decisions such as to expand Medicaid so that the rate of uninsured can be reduced thereby mitigating the risk of closures to some extent (Stone).

1.4.3 Research Objective 3: Deployment and Evaluation of Quality Improvement Initiatives

As mentioned above, to prevent further closure of hospitals in the future, hospitals need to make quick decisions to save themselves from closing their doors. At this time, one of the rational solutions to overcome this situation is to create improvement action plans to reduce costs and, increase revenue and profit. One of the enablers to make the suggested improvement initiatives is by deploying Lean Six Sigma in hospitals.

In this component of the research, Lean Six Sigma projects are identified and corresponding cost savings are quantified. The projects are then selected with an objective of maximizing cost savings to be deployed in the hospitals including in disadvantaged locations within an enterprise system. By doing so, the deployed projects are expected to generate cost savings for hospitals and thereby reduce the financial vulnerability of the hospitals and making the hospitals self-sufficient to manage their operations. In the long run, it will enable hospitals to attract more patients, creating more revenue making opportunities and help become more financially viable. It will also provide immunity to a larger extent that any policy decisions or the adverse conditions that prevail outside the hospital will not affect it.

Chapter 2

Background

This chapter is organized such that first three sections discusses the changes and events that took place since healthcare reform was enacted in 2010. The sections that follow identifies and discusses the relevant research from the past through literature study.

2.1 Transitioning from Fee for Service to Value Based Reimbursements

As mentioned earlier, with the new reform in place, hospital reimbursements are being transitioned to value based performance rather than the traditional fee-for-service in which the hospitals and physicians were paid based on the number of services and time spend irrespective of the outcome of the treatment. The Centers for Medicare and Medicaid (CMS) has made some decisive initiatives to tie in 30% of the payments to Accountable Care Organization (ACO) or bundled payments by 2016 and reach 50% in 2018.

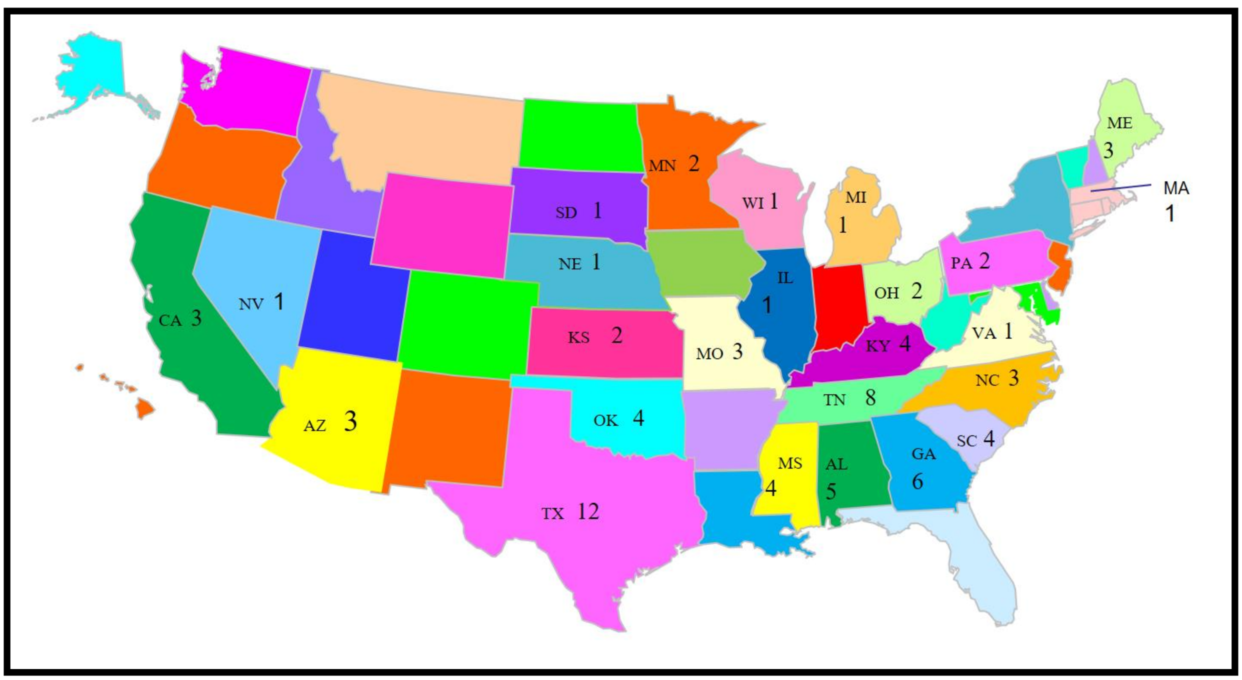


Figure 2.1: Rural Hospital Closures around US since 2010-2016 Note: Updated October 2016

Also, 85% of all traditional Medicare payments will be tied in to quality or value by 2016 and 90% by 2018 through Hospital Value Based Purchasing (HVBP) and HRRP (Brown).

The underlying reason for the transition is to bring changes to the way care is delivered in order to avoid adverse patient outcomes and expensive and/or unnecessary patient hospital stays and treatments. The transition from the fee-for-service reimbursement system to one based on value is currently one of the greatest financial challenges health systems face (Brown and Crapo). Those hospitals that will not be able be perform on par will be cited, and subsequently face financial problems. Some of the initiatives such as the HVBP, ACO, bundled payment, and clinical integration are already in place to streamline the transition. In order to asses a hospital's performance, proper measures need to be in place and for many years, providers have submitted their performances for quality measures programs such as Hospital Inpatient Reporting System, Hospital Outpatient Quality Reporting and Physician Quality Reporting System. The value based reimbursement programs and HRRP programs will rely heavily on those measures to assess the performances of hospitals.

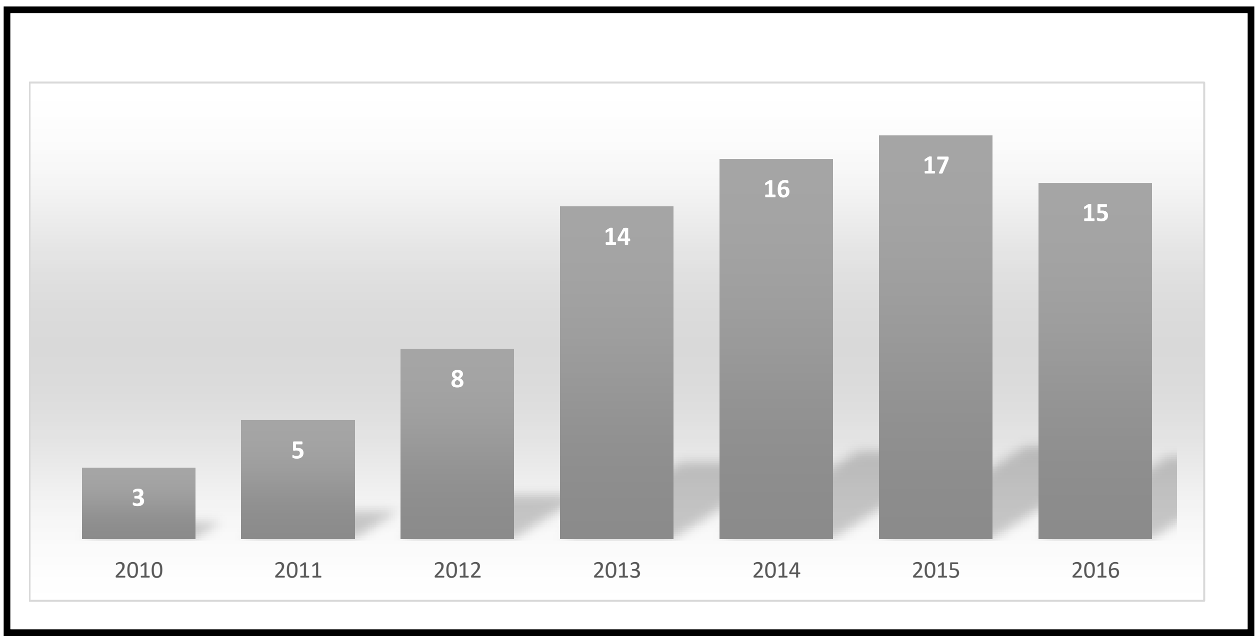


Figure 2.2: Rural Hospital Closures by year Note: Data for 2016 year is from January-October

The next two sections illustrate two important programs that determine the reimbursement decisions based on hospitals' performances.

2.1.1 Hospital Value-Based Purchasing (HVBP)

One of the initiatives to tie in quality with reimbursements is the HVBP which was enacted in Section 3001(a) of the Affordable Care Act. HVBP is based on the performances of the hospitals on the hospital quality data reporting infrastructure developed for the Hospital Inpatient Quality Reporting (IQR) Program. Total Performance Score (TPS) is calculated for hospitals based on their performances on a set of measures from the IQR program. The HVBP program includes several measures on different domains including selective processes of care measures (Processes of Care Domain), patient satisfaction surveys (HCAHPS Domain), Mortality rates (Outcome Domain) and Medicare spending per beneficiary (Efficiency Domain). CMS has designed to fund this program by deducting Diagnosis-Related Group (DRG) payments for the applicable first year from participating hospitals. Hospitals can earn back the deducted amount in equal amount, greater or even lesser depending on their TPS. The scheduled DRG deductions commenced in 2013 with 1% and, 1.25% in 2014, 1.5% in 2015, 1.75% in 2016 and will reach 2% in 2017.

Table 2.1: Rural Hospital Closures by State from 2010-2016 Note: Updated October 2016

S. No	State	Number of Hospitals closed
1.	Alabama	5
2.	Arizona	3
3.	California	3
4.	Georgia	6
5.	Illinois	1
6.	Kansas	2

Table 2.1 Continued

S. No	State	Number of Hospitals closed
7.	Kentucky	4
8.	Maine	3
9.	Massachusetts	1
10	Michigan	1
11.	Minnesota	2
12.	Mississippi	5
13.	Missouri	3
14.	Nebraska	1
15.	Nevada	1
16.	North Carolina	3
17.	Ohio	2
18.	Oklahoma	4
19.	Pennsylvania	2
20.	South Carolina	4
21.	South Dakota	1
22.	Tennessee	8
23.	Texas	11
24.	Virginia	1
25.	Wisconsin	1

2.1.2 Hospital Readmission Penalties and Implications:

One of the other performance measurement programs to tie in quality with reimbursement from CMS is the HRRP, where the hospitals are penalized for excess readmissions for the same diagnosis within a 30-day period. The acceptable readmission rates are based on averages calculated at a national level and those hospitals that have readmissions higher than the accepted level, are penalized up to 3% starting FY 2015. Launched in 2012, CMS fined hospitals with a maximum penalty of 1% in FY 2013, 2% in FY 2014 and 3% during FY 2015, CMS started HRRP with three measures on health conditions including Heart Failure, Heart Attack and Pneumonia. At present, the measures also include Chronic Obstructive Pulmonary Disease (COPD) and Hip/ Knee replacement conditions. In 2013, 18% of Medicare patients, which is roughly around 2 million patients returned to the hospitals within 30 days with an estimated annual cost of $26 billion and $17 billion alone that could have been avoided (Rau). During the same year, CMS fined 2213 hospitals for $280 million in penalties, which represents 0.3% of total Medicare base payment, with 276 hospitals receiving a maximum of 1% penalty (Brown). In 2014, 2225 hospitals were penalized for $227 million which represents 0.2% of total Medicare base payment with 1074 hospitals receiving the maximum penalty of 2%. 1371 hospitals received lower penalties and the average penalty decreased from 0.42% to 0.38%. for year 2015, 2610 hospitals were assessed for penalties with the average penalty increasing from 0.38% to 0.63% with 39 hospitals receiving a maximum penalty of 3% and the total fine amount estimated to be $428 Million.

As we can see from the above data, the second year had a drop in the total penalty amount but there was a rise in fine amounts for year 2015. It may be because two new measures were added in 2015. It is also important to note that even though a hospital may have improved from previous years in terms of reducing the readmissions rate, the hospital is still penalized if the readmissions are above the acceptable level (i.e., perform poorly compared to other hospitals).

Despite growing concern that the Medicare and Medicaid funding pays well below the actual costs of care, readmission penalties add a large burden on top of the existing problems in which the hospitals are experiencing. Rural hospitals are particularly affected as they depend on 45% of Medicare payments for their total annual income and there are already closures reported due the reimbursement cuts (Janney). Also, rural areas usually tend to have poor and less educated residents with a lack of primary care physicians which exacerbates the situation and undermines the efforts of treating hospitals to avoid penalties.

Hospitals discharging patients have already taken measures to curb the returning of patients within a 30-day window. Hospitals have invested in transitional care activities such as discharge follow up, reconciling medications, partnering with other local hospitals or care facilities and performing follow up phone calls (Bradley *et al.*, McIlvennan *et al.*). Some hospitals care for returning patients without readmitting them overnight so that Medicare does not count their cases, while some other hospitals are replacing perfunctory discharge plans by giving paper instructions to patients and giving medications to those who cannot afford them. Some hospitals even send the nurses to patient homes to ensure the patients are taking care of themselves (Rau). While big hospitals can afford to manage the above mentioned services to avoid patients coming back, it is almost certain that small and financially strained hospitals may not have the resources available to manage the patients once they leave the hospital. Thus, the above stop gap arrangements may work for a while, but there is a need for a permanent solution.

An important note that must be considered here is that in years 2013 and 2014, many hospitals that were punished were the ones which served a majority of low income patients in which 77% of the hospitals with the highest share of low-income patients were penalized for excessive readmission during the first year versus just 36% of hospitals with the fewest number of poor patients. Also, the Medicare Payment Advisory Commission (MedPAC) has found that the hospitals that serve destitute people are the ones with highest number of readmissions. Some experts believe that the safety-net hospitals that treat underprivileged patients should not be classified the same as other hospitals. Safety-net hospitals are more vulnerable to receiving more penalties than other hospitals. This further attenuates the potential profitability and increases the debt of these hospitals. A review conducted by the University of Texas has found that patients that are elderly, minority, poorly educated, poor, smokers have high readmission rates. The safety net hospital patients are more prone to challenges in taking care of their health. The MedPAC has in fact urged the government that it should compare hospitals of equal status when assessing penalties. While the bills are pending in both houses of congress that would make Medicare consider socio-economic status of a hospital's patients while calculating fines, the Obama administration has raised concerns that assuming safety-net hospitals will do poorer in avoiding readmissions might encourage lower expectations for the quality of care for low income patients (Rau).

2.2 Reduction of Disproportionate Share Hospital (DSH) Payments

The safety-net hospitals are predominantly used by the uninsured and poor. When these patients visit the hospital, and are unable to pay, it becomes a bad debt for the caring hospital. Furthermore, by law, when a patient ends up in an emergency care, regardless of the patient's ability to pay, the hospital must provide treatment for the patient until they are stabilized or they die. In these scenarios, again it becomes a debt for hospitals that it may have to take care of those costs by themselves.

Before the PPACA was in place, the federal government made special arrangements to deal with the above kind of situations by having a program known as "Disproportionate Share Hospital (DSH) Payments". By this program, funds are allotted to hospitals for covering the unmet expenses to prevent further financial strain. But after the PPACA program was implemented, funds from the DSH program have been reduced by about $546 Million in 2014, $1.25 Billion in 2015, compared to 2014 and further $1.2 Billion reduction in 2016, compared to 2015 (American Hospital Association). The underlying basis for the reduction of funds is that since Medicaid has been expanded for many new patients along with the PPACA, the government assume that the previously uninsured people would now be covered by Medicaid, thereby increasing the revenue of the hospitals and hence the uncompensated costs would eventually come down. But unfortunately, not all the 50 states have accepted to expand the PPACA in their states and some states had declined the federal mandate.

Along with the DSH payments, these small hospitals have been historically supported to provide care despite of their low operating margins by charity donations and other support from respective state government. But the changes in the health reform seems to have affected those funding sources by either reducing it or by completely stopping them.

An example of this is Grady Memorial Hospital in Atlanta, where the patients that present to emergency rooms of neighboring hospitals are often sent to Grady Memorial Hospital. As the major safety-net hospital of the metropolitan Atlanta area, but also the only Level 1 trauma hospital within a 100 mile radius of the Atlanta area, Grady Memorial Hospital requires significant funding to maintain its functionality as a Level 1 trauma facility. Previously, the hospital was heavily funded with DSH payments, but recently it has been hit with a stream of PPACA penalties for its slow emergency room service to the poor in non-life threatening situations.

2.3 States Declining Medicaid:

In spite of unfavorable events after the implementation of PPACA, some states have already declined the expansion of Medicaid. As of September 2016, 19 states have declined the expansion of Medicaid, leaving 4.5 million people uninsured (Garfield). The refusal came only after the Supreme

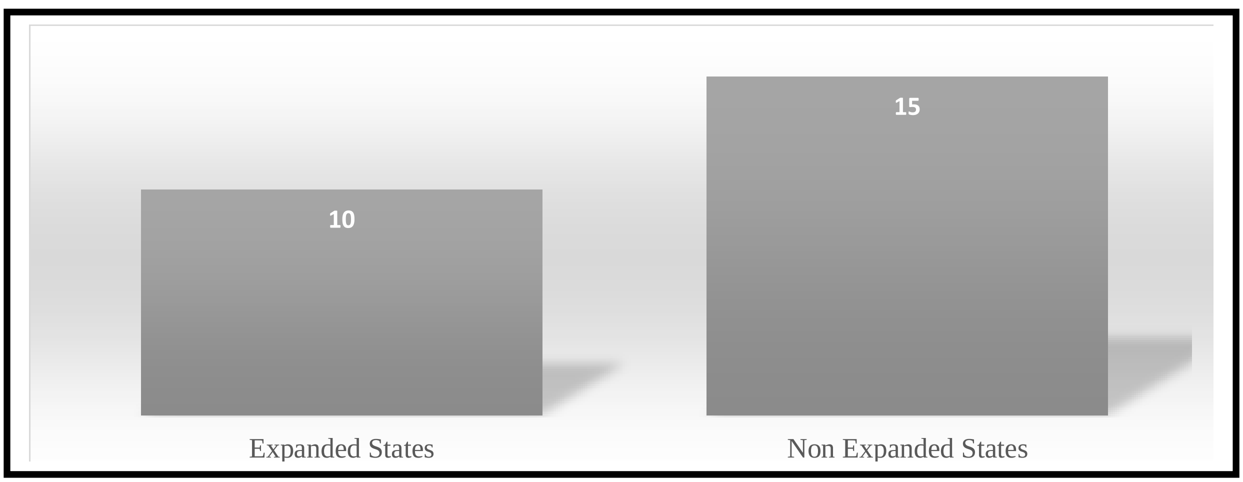


Figure 2.3: Medicaid Expanded & Non-Expanded States experiencing closures in U.S, 2010-16(October)

Court in 2012, upheld the constitutionality of the PPACA's mandate of requiring majority of the people to have minimum health insurance coverage starting in 2014.

States that accepted to expand Medicaid program are implemented through the joint efforts of the federal government as well as the respective state government. From 2014 until 2019, the federal government would pay most of the cost of the expansion up to 100% and from 2020, the states will be responsible to pay 10% of its costs.

According to a study from RAND Corporation, the cost of expanding Medicaid is lower than the expense for providing uncompensated care to uninsured residents after the implementation of PPACA. The RAND study also reveals an estimate of about 9,000 deaths would occur annually if the states would not expand Medicaid. Another study from University of North Carolina reveals that the number of hospitals closed are more in the states which did not expanded Medicaid than the ones which expanded. But on a different note, there is a shift in the revenue mix such that the commercial reimbursements had dwindled over the years and the government reimbursements have gone up for the same years. The

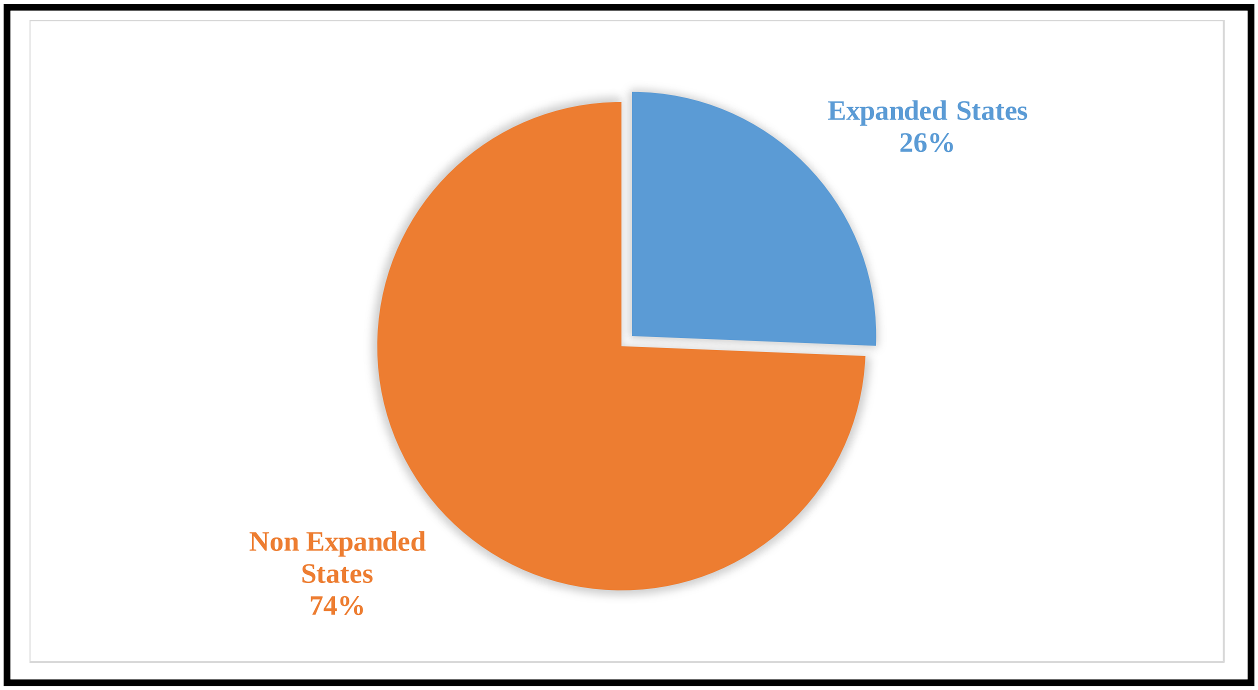


Figure 2.4: Percentage of Hospitals closed in Medicaid expanded & non expanded states 2010-16(October)

change in revenue mix impacts a hospital's bottom line because reimbursements from Medicare and Medicaid are not equivalent in comparison with the reimbursements from private insurance payers. It also suggests that the hospitals with a good revenue mix from private and government reimbursements may escape this financial crunch and only the hospitals which depend on government reimbursements for majority of their revenue will face difficulties.

The PPACA supporters as well the state representatives from states which implemented PPACA, has their own contention of accepting the Medicaid expansion. The proponents believe that the PPACA would 1. Alleviate the uncompensated costs, the burden which the hospitals and the states are managing 2. Reduce costs 3. Reduce the burden on the tax payers who are generally obligated to cover the uncompensated costs by paying special taxes in some states 4. PPACA would create jobs when the hospitals start picking up patients on primary care, thereby the demand for workers would be more and hence creating new opportunities 5. Costs of implementing Medicaid would be less than the cost burden due to uncompensated care and 6. Improve patient outcome.

Alternatively, the states that rejected the PPACA has their own contentions as well. Some of the important states that reject the expansion includes Florida and Texas. In fact, Texas have the most number of uninsured patients in the country. According to Rick Scott, Governor of Florida, contended that the PPACA would strain the state budget and it can be implemented only after raising taxes. Also, the permanent relief can be achieved after sorting out ways to reduce healthcare costs and expanding job opportunities for people to afford private insurances.

Although some states did not chose to expand Medicaid, their state residents will still be subjected to taxes, fees and other revenue provisions of the PPACA and have the big chance of losing the funds allotted for the Medicaid payments. However, some states have made alternative arrangements to expand Medicaid by paying private insurance companies using the amounts earmarked for Medicaid (Turner & Roy). Whatever decision the states make to either accept or reject the expansion, the bottom line is that the common people is the one who will benefit or suffer with their state representative's decision.

In the following sections, the factors identified based on the background study will further be discussed in detail through literature sources.

2.4 Hospital Closure- Discussion of Financial Importance Factors

Several factors play a role to bring a hospital to its brink of stopping its operations. Majority of the times, hospitals are closed when they are no longer financially viable to provide care for the patients. When a hospital is not able to yield revenue to surpass or even match the costs incurred, the hospitals finds it hard to continue their services. Many hospitals in rural areas operate as non-profit hospitals making little to no profit and in many cases, they operate on negative margin and sustain just for the sake of having healthcare coverage for rural patients.

Traditionally, rural areas are usually said to have low population density which affects the hospital utilization rate. There were 34 hospitals that was closed in 2013 which had an occupancy rate of 34% compared to 48% in the nearest open hospital (Peck). Also in 2013, in comparison with urban hospitals for hospitals with less than 100 beds, the occupancy rates for rural hospitals were 37% while the urban hospitals' occupancy rates were 63% ("Rural Hospitals Continue to Struggle"). There have been several hospitals closed or have converted in to ambulatory, outpatient care and emergency care centers due to low occupancy rates (Evans). The other reasons said for the low occupancy rates is because of the people's perception that the quality of care in rural hospitals is low and they travel to their nearest urban hospital for care.

Many rural hospitals tend not to have a good payer mix, with majority of the patients having Medicare insurance, which is believed to pay not to match the costs incurred by the hospitals. Circumstances like this do not provide hospitals to make profits and instead are pushed to financial difficulties.

(Kaufman *et al.*) researched rural hospital closures and identified factors affecting negative operating margin. The researchers found % of families 65 and under, % families below poverty, patient to hospital (10 miles), nearest hospital with more than 100 beds (per 10 miles), outpatient/total revenue, Medicare inpatient payer index, Medicare outpatient payer index, Occupancy rate, Obstetrics and Surgery volume to be the significant contributing factors.

(Thompson *et al.*) in their paper, examined how the Medicaid expansion have affected insurance coverage in rural areas and how it would differ if each state tried to expand Medicaid. The research has found that the number of uninsured population have considerably came down after expansion and the states which did not expand Medicaid will likely to be affected with little to no medical coverage.

The other relevant research from (Reiter *et al.*) focused on the uncompensated care provided by the hospitals in rural and urban areas and more importantly found the differences between states that expanded Medicaid and the ones that refused expansion. In their research, hospitals have been classified as Critical Access Hospitals (CAH) and other rural hospitals for both type of states (states expanded Medicaid and not expanded). The authors have calculated the total uncompensated costs as a sum of unmet costs due to Medicaid, Children's Medical Insurance Program (CHIP), unreimbursed costs of other indigent care, bad-debt expense and charity care cost. The results from their research shows that the total uncompensated care costs are higher in states that expanded Medicaid, but the uncompensated costs that incurred only due to uninsured and underinsured were higher in the states that did not expand Medicaid. The authors overall research suggests that the hospitals in the states that did not expand Medicaid is more financially vulnerable and have more financial pressure and losses.

Getting covered with health insurance is quintessential both for patients as well as hospitals. It helps the patients to avoid paying hefty sum of treatment costs and enable to pay very little up front for the care. It protects the hospitals from ending up with bad debt by caring for disproportionate number of patients who are unable to pay for their care. It is evident from the above research that many hospitals in rural areas, especially in the states that did not expand Medicaid may likely to suffer from loss of revenue, given the poverty conditions in rural areas and many people without health insurance.

Presence of particular race such as disadvantaged and Hispanic population is believed to affect the closure of hospitals. (Hsia and Shen) earlier studied the Trauma center closures and how it disproportionately burdens the vulnerable populations. They both studied the trauma centers that was closed between 2001 and 2007 with an objective to determine if the driving distances for socioeconomically disadvantaged, racial and ethnic minorities to their nearest trauma centers, improved or deteriorated. Their studies revealed that by 2007, sixty-nine million population had to travel farther to find the nearest trauma center than they did in 2001. This deterioration in geographical access has been more acute in communities where disadvantaged population live. This study also revealed that the rural communities have a higher risk of experiencing declines in geographical access than urban communities. While this research informs us that more trauma centers have been closed in disadvantaged areas, it is yet to know, the association between disadvantaged population and hospital closures.

The research by (Bazzoli *et al.*) evaluated the closure of “Safety net hospitals” (which are predominantly used to treat low income, poor and uninsured patients) and its effects on uninsured, Medicaid patients and racial/ethnic communities. Their research suggested that certain groups of uninsured and Medicaid patients experienced greater disruptions in care, especially the Hispanic uninsured and Medicaid women hospitalized for births. Here same as the disadvantaged population in earlier research, although the relation between closure and Hispanic population is not yet known, it can be inferred that there may be a relation between presence of large Hispanic population and hospital closures.

2.5 Hospital Closure-Discussion of Operational Importance Factors

Traditionally, hospital closures are associated with many external factors that causes financial instability for hospitals. It is true for large extent that the conditions that exists outside the hospital have big influence in deciding a hospital’s ability to stay and offer care services, especially in rural areas. But in recent times, hospitals’ internal operational characteristics has been under severe scrutiny with new programs in place through the healthcare reform. Hospitals operating on “RED”, i.e., on negative margin will financially strain further with reimbursements cuts and penalties as these reimbursement deductions can be translated in to hundreds of thousands of dollars for which the hospitals cannot afford to lose, as losing reimbursements will most likely worsen their situation and will catalyze the closure decisions.

On this juncture, there is little to no evidence so far on the association between the quality of hospital care processes and the likelihood of hospitals to get closed. (Spade and Strickland) on their paper titled "Rural Hospitals Face Many Challenges in Transitioning to Value-Based Care" have described the struggle of small non-profit hospitals since changes has been brought in the hospital reimbursements to value based payments and in effect, the authors have mentioned that balancing finances will be difficult during this period and hospital leaders must make difficult decisions regarding it. Also, to overcome the changes, hospitals must innovate, restructure, become more efficient and continuously improve care to protect community safety net. The authors also predicted mergers, shared service partnerships, realignment of services towards outpatient and ambulatory care, conversions of acute care hospitals in to community-focused health care organizations and in some cases, closure of hospitals with additional reimbursement cuts. Previously, (Ly *et al.*) identified the relation between the hospitals' margin and the quality of care as well as hospitals' margin and change of status (closures, mergers etc.). This research has found that the hospitals performing at the top 10% level of operating margin had higher summary performance indicator score for Heart failure and Pneumonia conditions compared with the hospitals at the bottom 10% level of the operating margin. The above results are same for readmissions as well such that the hospitals within the top 10% level of operating margin had lower readmission rate for Acute Myocardial Infarction and Heart Failure conditions compared with the hospitals at the bottom 10% level of operating margin. This research has also found that the hospitals with low operating margin tend to close, merge and got acquired.

(Hung *et al.*) evaluated the rural, urban differences in the proportion of hospitals that received readmission penalties as well as the condition specific readmission rates for both and found that rural hospitals were penalized more than the urban hospitals. Also, both rural and urban hospitals that are present in the communities with fewer primary care physicians, low family income, low education levels and higher proportion of population with ages >65 are more likely to be penalized.

(Goldman and Dudley) studied the rural and urban hospital differences in adherence to 10 hospital compare measures on Acute Myocardial Infarction(AMI), Heart Failure(HF) and Community Acquired Pneumonia(CAP) and have found that rural hospitals had low adherence in 6 AMI and HF measures.

2.6 Deployment and Evaluation of Quality Improvement Initiatives

Project Selection and Prioritization play a vital role in the successful deployment of Lean Six Sigma initiatives in a company. Considerable attention must be paid to make careful evaluation of projects for the initiatives to be successful.

(Antony and Banuelas) identified success factors for effective Six Sigma implementation and found a. Management Involvement and Commitment b. Cultural Change c. Organization Infrastructure d. Training e. Project Management Skills f. Project Prioritization and selection, reviews and tracking g. Understanding the Six Sigma methodology, tools and techniques h. Linking Six Sigma to business strategy i. Linking Six Sigma to customer j. Linking Six Sigma to human resources and k. Linking Six Sigma to suppliers. These factors were found to be critical factors for the Six Sigma implementation to be effective. (Antony) did a comparative study between manufacturing and service processes from Six Sigma perspective and noted project selection process should follow Voice of the customer, Voice of the process and Voice of the Strategic business goals. The author also suggests some guidelines for selecting Six Sigma projects as a. Linking to strategic business plan and organizational goals b. Sense of urgency c. Selecting projects which can be completed in Six months d. Projects to be clear, succinct, specific, achievable, realistic & measurable e. projects have support and approval of senior management f. project deliverables in terms of their impact on one or more critical characteristics such as critical to quality, critical to cost and critical to delivery and g. project selection based on good metrics.

(Kumar *et al.*) focused on the importance of project selection process and its role on successful deployment of Six Sigma. They proposed a hybrid methodology to select projects using analytical hierarchical process and project desirability matrix.

(Dinesh Kumar *et al.*) proposed to identify Six Sigma projects using Data Envelopment Analysis(DEA) to maximize the benefit for the organization by identifying important inputs and outputs for Six Sigma projects. (Hu *et al.*) developed a multiple objective formulation using a goal programming approach for project portfolio selection in manufacturing companies. (Yang and Hsieh) proposed a Six Sigma project selection method using national quality award criteria and Delphi fuzzy multiple criteria decision making method. The authors have proposed to use national quality award criteria as the Six Sigma project selection criteria and the strategic criteria were evaluated using a Delphi fuzzy multiple criteria decision making method.

(Padhy and Sahu) developed a two-staged methodology for project portfolio selection. In the first step, a real option analysis for evaluating the value of the projects to improve management flexibility was used and in the second step, a zero-one linear programming model for selecting and scheduling an optimal project portfolio based on organization's objectives and constraints was proposed.

Chapter 3

Methodology

This first section of the Research Methodology illustrates the detailed steps under each of the three research objectives

3.1 Research Objectives and Specific steps

Research Objective #1

Identify Hospital Closure Factors based on Financial and Operational Importance.

Step 1: Identify the hospital closure risk factors

Step 2: Identify the factors that cause the risk of hospital closures based on financial importance

Step 3: Identify the factors that cause the risk of hospital closures based on Operational importance.

Research Objective #2

Evaluate the hospital closure risk factors to determine the likelihood of causing closures

Step 4: Use Statistical methods to evaluate the factors that may cause risk of closures based on financial Importance

Step 5: Use Statistical methods to evaluate the factors that may cause risk of closures based on operational Importance

Step 6: Use Statistical methods to evaluate the factors that may cause risk of closures based on combined importance

Research Objective #3

Deployment and Evaluation of Quality Improvement Initiatives

Step 7: Identify Lean Six Sigma projects to be implemented in hospitals throughout Hospital Enterprise System

Step 8: Select identified projects based on maximizing cost savings

step 9: Run scenario 2 by adding disadvantaged location factor to the model

Step 10: Select projects to optimize cost savings

Step 11: Evaluate the benefits for the Hospital Enterprise System.

In the next following sections, each Research Objective is discussed further in detail.

3.2 Research Objective 1: Identifying the Hospital Closure Risk Factors based on Financial and Operational Importance

During the background research, a comprehensive search for hospital closure risk factors was performed from journal literatures, online and print news article reports, televised news reports, as well as other social media and print resources. Several factors that have caused the risk of closures were identified, especially, the recent literatures, news reports and articles highlighted shrinking Medicare reimbursements and other financial assistances over the few years were highlighted as one of the primary reasons for closures, although it did not exactly pin point the exact factors that drove the decisions to reduce financial reimbursements for hospitals. Other factors such as market competition, presence of certain race etc. were also identified as the potential reasons for hospital closures.

As discussed earlier, based on the factors that were identified, it was determined that the closure risk factors can be categorized in to two divisions., namely financial importance and operational importance.

3.3 Research Objective 2: Evaluating the Risk Factors to Determine the Likelihood of Causing Closures

The goal is to evaluate the factors that will actually cause the risk of hospital closures, especially the rural hospitals that were closed in the past few years by creating a prediction model. i.e., to identify the independent predictors, which will cause the risk of closure of hospitals and can predict closures in the future. The response variable in the model is a binary variable i.e., closed/not closed. For this purpose, a

Logistic Regression Model is used to relate the binary dependent variables with the independent continuous variables.

3.3.1 Data Collection:

Operational importance factors were collected from Hospital Compare website, a portal which has information on quality of the care provided by Medicare certified hospitals, which was created as a joint initiative between Medicare and Hospital Quality Alliance. Hospital Compare provides information on how well the hospitals provide recommended care on various constructs including processes of care measures and outcome measures for multiple health conditions such as Heart Attack, Heart Failure, Pneumonia, Surgery and other complications as well as patient's experience of hospital care. The Federal programs such as HRRP, HVBP etc. uses hospital compare measures' data for making decisions regarding penalties and payment reductions based on the performances of the hospitals on those measures.

Financial Importance data were collected from Area Resource File, which contains county, state and national database files.

3.4 Discussion of Independent Predictor Variables

3.4.1 Operational Importance Model:

The objective of the operational importance model is to evaluate hospital performances on core measures that determine penalties, reimbursement cuts and incentives based on appropriate performances of the hospitals. Further, this model will provide a framework for hospitals to target the core measure processes to improve and realize the benefits. Based on HRRP and HVBP programs, several measures for prominent health conditions including Heart Attack, Heart Failure and Pneumonia as well as many patient experience survey measures were identified.

The HRRP program measures include Readmissions for Heart Attack, Heart failure and Pneumonia conditions.

The HVBP program contains (i) Process of care measures- many including Discharge instructions for Heart Failure patients (HF-1), Blood culture performed in the Emergency Department prior to initial Antibiotic received in hospital (PN-3B), Initial antibiotic selection for Community-Acquired Pneumonia in Immunocompetent patients (PN-6) which are critical such that these selective processes can prevent adverse patient events, (ii) Outcome of care measure measures, which is believed to be an indicator for the poor quality of care by the hospitals, includes mortality rates for Heart Attack, Heart failure and Pneumonia (iii) The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) Measures are typically a survey of patient satisfaction, based on patient experiences during their hospital stay. Measures inclusive of Doctor communication, Nurse Communication, Pain management, Hospital cleanliness, Explanation on medication given, Discharge Instructions, Patient's recommendation for the hospital are being used.

Table 3.1**:** Hospital Readmission Reduction Program Measures

Variable	Variable Description
Heart Failure Readmission	30-Day Readmission rate for Heart Failure Condition
Pneumonia Readmission	30-Day Readmission rate for Pneumonia Condition

Table 3.2: Hospital Acquired Condition Reduction Program Measures

Variable	Variable Description
Blood Infection	Central Line Associated Blood Stream Infections (CLABSI)

Table 3.3: Hospital Value Based Purchasing Program Measures

Variable	Variable Description
HF_1	Discharge instructions for Heart Failure patients
PN_3B	Blood culture performed in the Emergency Department prior to initial Antibiotic received in hospital
PN_6	Initial antibiotic selection for Community-Acquired Pneumonia in Immunocompetent patients
Pneumonia Mortality	30-day Pneumonia Mortality rates
No Doctor Communication	Percent of patients who reported that their doctors "Sometimes" or "Never" communicated well.
No Nurse Communication	Percent of patients who reported that their nurses "Sometimes" or "Never" communicated well.
No Pain Management	Percent of patients who reported that their pain was "Sometimes" or "Never" well controlled.
No Post Recovery Info	Percent of patients who reported that they were not given information about what to do during their recovery at home.
No Patient Recommendation	Percent of patients who reported NO they would not recommend the hospital.
No Immediate Help	Percent of patients who reported that they "Sometimes" or "Never" received help as soon as they wanted.
No Medication Instructions	Percent of patients who reported that staff "Sometimes" or "Never" explained about medicines before giving it to them.

3.4.1.1Discussion of Processes of Care Measure Variables:

3.4.1.1.a PN -3B (Blood culture performed in the Emergency Department prior to initial Antibiotic received in hospital).

This is a pneumonia process of care measure which focuses on treatment provided to emergency department patients prior to admission orders. Specifically, it targets the initial emergency room blood culture performed prior to the first dose of antibiotics. The reason for importance of this measure is that it is vital to determine the type of bacteria, virus or fungi for administering the right antibiotics. A higher rate of blood culture performed indicates that hospitals provides higher level of care to patients.

3.4.1.1.b PN-6 (Initial antibiotic selection for Community-Acquired Pneumonia in Immunocompetent patients)

The PN-6 is another pneumonia process of care measure which focuses on providing initial antibiotic treatment for pneumonia patients. The reason of importance of this measure is that to treat the pneumonia patients with appropriate antibiotic(s) for best care outcomes. A higher rate of antibiotics given to the patients indicates that hospitals provides higher level of care to patients. Failure to provide right antibiotic(s) results in prolonged length of stay for patients and increased costs for hospitals.

3.4.1.1.c HF-1 (Discharge Instructions)

The HF-1 is a Heart Failure care measure which aims heart failure patients or care givers to be provided with discharge instructions or educational material during discharge or during their hospital stay. The instructions provide information on activity level, diet, discharge medications, follow up medication etc. It is estimated that about 4.7 million patients have heart failure conditions in the country and failure to give patients with complete discharge instructions will likely results in higher rates of readmissions. In order to improve patient outcomes and reduce health care costs, this measure is given foremost importance in reimbursement decisions such as in HVBP programs.

3.4.1.2 Outcome of Care Measures

3.4.1.2.a 30-day Readmission Rate

Hospital 30-day readmission measures are unplanned readmissions, in which patients return to the hospital for the same diagnosis within 30-day period after discharge. In general, it is believed that one of the ways to improve quality and reduce health care costs is to avoid the unplanned 30 day readmissions and the hospitals which has higher than normal readmission rates will be penalized for poor quality with the HRRP program. Rate of readmission penalties has increased from 2% to 3% recently and rural hospitals depend on 45% of their annual revenue from Medicare. With penalties consuming up critical hospital reimbursements, it is highly likely that the hospitals will be financially stressed and will increase the risks of closure.

3.4.1.2.b 30-day Mortality Rate

A 30-day Mortality rate are estimates of deaths within 30 days of a hospital admission, for patients hospitalized with one or more medical conditions. Mortality rate measures indicate if the hospitals are doing well in preventing complications, educating patients on their care needs and helping patients to make smooth transition from hospital to home or another type of care facility. This measure is an important factor since it is one of the measures used in HVBP program in which higher performances on this measure will yield incentives and bad performances will result in reduced reimbursements,

3.4.1.3 HCAHPS Measure

The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) Measure is an initiative to provide a standardized survey instrument and data collection methodology for measuring patient's perspectives on hospital care. It contains a core set of questions that can be combined with a broader, customized set of hospital-specific items. These surveys are designed to produce comparable data on the patient's perspective of care that allows objective and meaningful comparisons between hospitals on domains that are important to hospitals (CMS). The HCAHPS survey measures are used in HVBP program as well which will enable hospitals to earn incentives for good patient perception of care and hospital or reduced reimbursements for poor patient satisfaction scores.

3.4.1.4 Hospital Acquired Condition (HAC) Reduction program:

This program was enacted along with the PPACA reform to incentivize hospitals to reduce Hospital Acquired Conditions. Starting from year 2015, hospitals are penalized by 1% who are among the lowest performing 25% on the HAC measures.

3.4.2 Financial Importance Model:

The objective of the financial importance model is to underscore the importance of certain factors that can prove detrimental for the functioning of vulnerable hospitals and how states can leverage the healthcare reform to address those factors. With 74% of the rural hospitals that was closed in the country where from the states that did not expand Medicaid, this financial importance model will help the states authorities to reconsider their decision on to whether they can expand Medicaid to expand health coverage for the

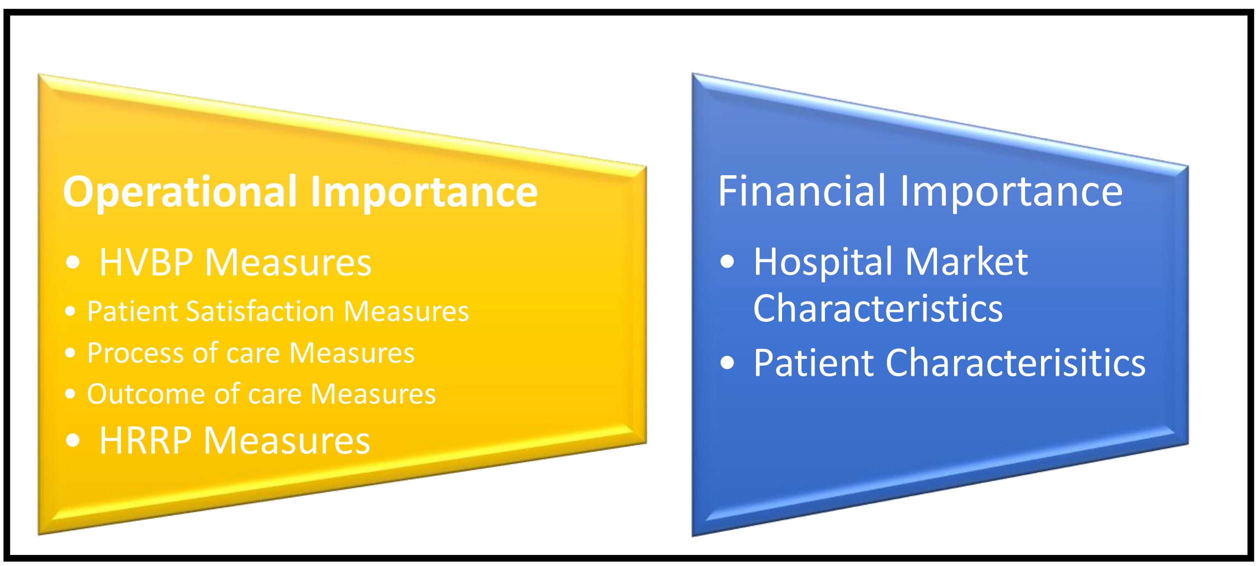


Figure 3.1: Operational and Financial Importance Variables

needy populations. If not all factors can be addressed now, few vital factors such as hospitals located in areas where many people live without health insurance, have low income such that they cannot afford proper care can be addressed. Provisions are made in the reforms to tackle these concerns such that it gives health coverage for these specific populations thereby reducing the financial problems faced by the hospitals and further reducing the risk of hospitals getting closed in the future.

3.4.2.1 Discussion of Financial Importance Variables:

3.4.2.1.a High Uninsured Population

Presence of many uninsured populations in a hospital locality is a major threat for hospitals. Big proportions of insured people may force hospitals to provide large uncompensated costs as rural areas usually tend to have poor and uninsured people who cannot afford care. Two third of the uninsured people live in states that did not expand Medicaid and identifying it may help in future policy decisions for the coverage of uninsured people (Newkirk).

3.4.2.1.b Number of Hospitals

High market share is a threat for hospital existence as more the number of hospitals in a given locality, more the risk of hospitals to lose revenue from the patients. In recent years after reform, patient can make informed decisions to choose a provider based on the performance of hospitals in the past. Hospitals will need to vie for attracting patients without losing to competitors. Although hospitals are sparsely located in rural areas, this factor still poses a threat for the closure of hospitals.

3.4.2.1.c Median Household Income

Median household income of the population in a given hospital locality may indicate the characteristics of population that live. In general opinion, patients with higher household income may have better insurance coverage such as third party private insurance coverage so that hospitals can get better reimbursements and less chances for hospitals to incur uncompensated costs. On contrary, patients with low household income may likely have little or inadequate health coverage, which may be a financial burden for hospitals to treat such patients.

3.4.2.1.d Population Estimate

It is a well-known fact that rural areas tend to have low population density compared to urban areas. Hence, it is more likely that the rural hospitals will have low patient revenue due to low patient utilization and that may cause the risk of driving the hospitals to closures.

3.4.2.1.e Race:

Race is a market characteristic variable that would be of the interest in this study. One of the previous research has identified that the emergency departments are more likely to be closed in disadvantaged locations (Hsia, Kellermann and Shen). The comparison of open and closed hospitals in this research will identify if there would be any association between the presence of a particular race and hospital closures. It can be noted that in 2015, the Hispanic and African American ethnicity contributed 29% of total uninsured population in US ("Uninsured Rates for The Nonelderly By Race/Ethnicity") and thus the chances of providing uncompensated care are more.

If this factor proves to be a reason for closure, it would also confirm the notion that the hospitals located in disadvantaged locations are left unnoticed by the hospital management for any improvement initiatives and would have greater chances of closure which causes increasing disparities for the disadvantaged population than making any initiatives to save these hospitals.

3.5 <u>Research Objective 3-</u> Deployment and Evaluation of Quality Improvement Initiatives

The goal of research objective 3 is to deploy quality improvement initiatives such as by using Lean Six Sigma management techniques at hospitals and evaluate how the improvements would reduce and prevent the risk of closures in the future in rural and in disadvantaged locations. At this phase, a hospital system encompassing three hospitals is identified for the study.

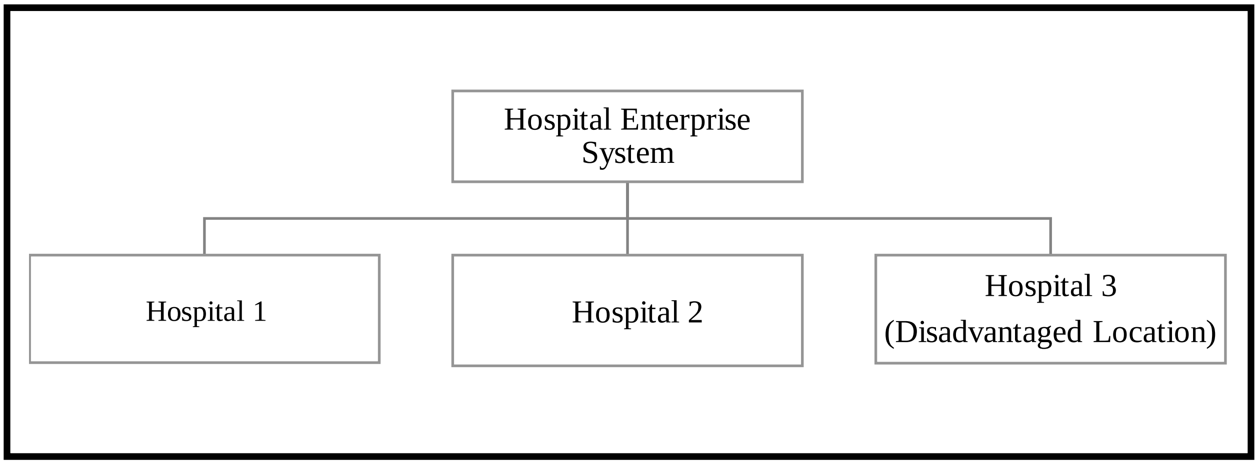


Figure 3.2: Hospital Enterprise System Model-Stage 1

Improvement initiatives in the form of Lean Six Sigma projects are deployed at these hospitals to realize the cost savings benefits attained at the enterprise level. The inclusion of hospital at the disadvantaged location will make sure that the hospital management will serve the population on those locations. The first step for the deployment initiatives is to identify Lean Six Sigma projects that can be implemented in the above hospitals. To do so, a complete search for Lean Six Sigma project implementations at hospitals was performed from journal literatures, magazines reports from American Society for Quality, Institute of Industrial and Systems Engineers etc., to identify various information such as the Project type (process(es) targeted), quantified savings from the project results, investment amount, tools used, Personnel type used (Yellow belts, Green belts, Black Belts), duration of the project etc. At this stage, the project opportunities (target process(es)) identified from literature are assumed to be identified from the hospitals and the projects were randomly assigned to three hospitals within the enterprise system identified above. Quantified cost savings data was adjusted for inflation to 2016 Dollar value using Consumer Price Index Inflation Calculator from Bureau of Labor Statistics. The data for investments costs for majority of the projects was not available from the literature. Hence the investment data was created using the cost savings data based on the Return on Investment (ROI) approach. Based on literature study, Six Sigma's ROI was estimated between 2:1 and 3:1. Hence, the investment cost of each project was randomly chosen between a range of $1/2^{nd}$ to $1/3^{rd}$ of cost savings from the corresponding project.

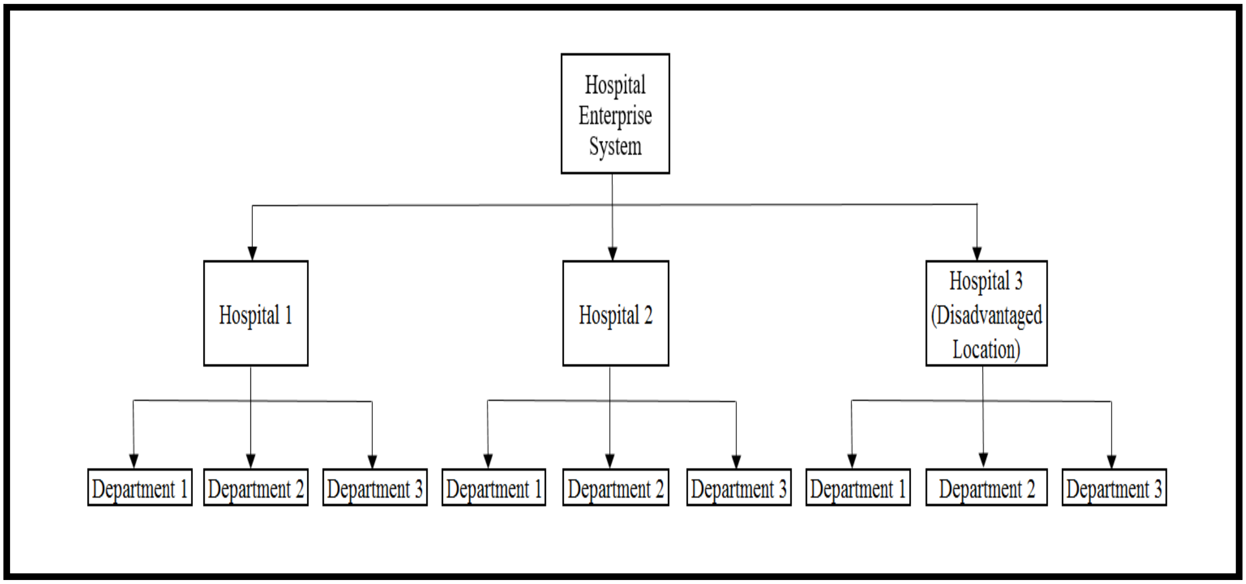


Figure 3.3: Hospital Enterprise System Model- Stage 2

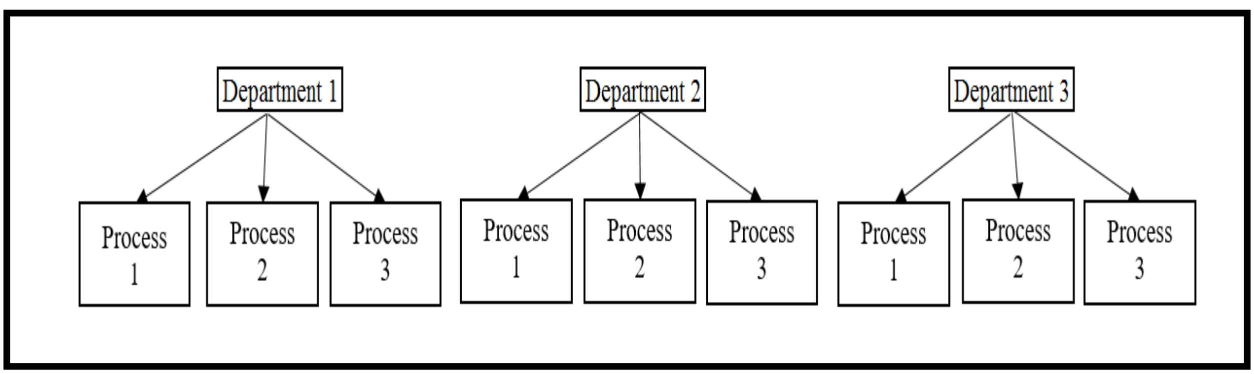


Figure 3.4: Hospital Enterprise System Model- Stage 3

The second step is the selection of projects to be deployed on pilot basis in the hospitals from the master list of projects identified from the previous step. A 0-1 Integer linear Programming (Knapsack) model is proposed for the projection selection approach with an objective of maximizing cost savings associated with the selected projects. Two scenarios were developed for maximizing cost savings modeling approach. In the first scenario, projects are selected from either one of the three hospitals which will maximize savings for the Hospital Enterprise system. In the second scenario, the third hospital is assumed to belong from a disadvantaged location and a factor is added to the model such that a certain minimum set of core measure projects are implemented in the disadvantaged hospital so that the hospital can improve its performance on core measures to avoid penalties, reimbursement cuts, reduce costs and develop opportunities for revenue.

3.5.1 Model Assumptions

If cost savings is in the range between \$0-\$100,000, the project is a Yellow belt Project.

If cost savings is in the range between \$100,000-\$250,000, the project is a Green belt Project.

If cost savings is above \$250,000, the project is a Black Belt project.

3.5.2 Model Objective Function

$$Max\ Z = \sum_{i=1}^{n} \sum_{j=1}^{m} X_{ij} S_{ij}$$

Here S_{ij} is the expected cost savings by deploying project *i* in hospital *j*.

X_{ij} is a binary decision variable if the project *i* is selected in hospital *j*. i=1,2,3…n., j= 1,2,3.

$$X_{ij} = \begin{cases} 1 & if\ the\ project\ i\ is\ selected\ in\ hospital\ j \\ 0 & if\ the\ project\ i\ is\ not\ selected\ in\ hospital\ j \end{cases}$$

3.5.3 Model Constraints-Scenario 1

In the following sections, the constraints for the model are discussed such that the projects are implemented in the hospitals within the Enterprise system, with three project types., Yellow belt, Green belt and Black belt projects. There is a limit for investment that the hospital enterprise management can allot for the overall project deployment which is set at $1M.

3.5.3 a Project Diversity Constraint:

Project diversity constraint refers to types of Six Sigma projects available such as yellow belt, green belt and black belt projects. Implementing yellow belt and green belt projects during the deployment phase will help organizations to realize benefits in a short span of time and get the trust from management as well as from stakeholders. Hence a minimum set of yellow belt and green belt projects are implemented in the initial phase of the deployment and is given by the following constraints

The constraint for implementing a minimum set of yellow belts project is given by

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}y_{ij} \geq Y_{ij}$$

Where y_{ij} is a binary parameter which decides if i^{th} project implemented in hospital j is a yellow belt project. Y_{ij} is the minimum set of yellow belt projects that needs to implemented in the pilot phase.

Likewise, the constraint for implementing a minimum set of green belt projects is given by

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}g_{ij} \geq G_{ij}$$

Where g_{ij} is a binary parameter which decides if i^{th} project implemented in hospital j is a green belt project. G_{ij} is the minimum set of green belt projects that needs to implemented in the pilot phase.

3.5.3. b Project Investment Constraint

The constraint for the model to maximize savings within an investment limit is given by

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}b_{ij} \leq B$$

Here b_{ij} is the investment required to implement project i in hospital j and B is the maximum allowable investment available.

3.5.4 Model Constraints-Scenario 2

3.5.4 a Disadvantaged location factor

As discussed above, a disadvantaged location factor is added to the model in scenario 2 by mandatory implementation of a set of core measure projects and is given by

$$X_{33}= 1$$

$$X_{23} = 1$$

$$X_{13} = 1$$

Here, X_{33}, X_{23} and X_{13} are projects are project 3 in hospital 3, project 2 in hospital 3 and project 1 in hospital 3 respectively.

3.5.4 b Blackbelt Resource Constraint

There is a limit in the use of number of black belts that the hospital system can use for implementing projects due to limited budget constraints. Hence the constraint is given by

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}a_{ij} \leq A_{ij}$$

Where a_{ij} is a binary parameter which decides if i^{th} project implemented in hospital j is a black belt project. A_{ij} is the maximum permissible number of Black belt resources that can be used.

3.5.4. c Project Investment Constraint

The constraint for the model to maximize savings within the maximum allowable investment is given by

$$\sum_{i=1}^{n}\sum_{j=1}^{m} X_{ij}b_{ij} \leq B$$

Here b_{ij} is the investment required to implement project i in hospital j and B is the maximum allowable investment available.

3.6 Research Hypothesis

Research question: What factors have caused the risk of hospital closures in rural locations and can strategic process improvement initiatives will alleviate and prevent further closure of hospitals in the future including in areas of disadvantaged population who need the most help.

The following sections illustrates the Research Hypotheses for Research Objectives 2 & 3.

Research Objective 2:

Independent Variables: Variable factors discussed in Financial and Operational Importance Models

Dependent Variable: Hospital Closed-1, Hospital Open-0.

Null Hypothesis: All of regression model coefficients are equal to zero.

(H0): $\beta_i = 0$ for all i

Alternative Hypothesis: At least one of the regression model coefficient is not equal to zero.

(H1): $\beta_i \neq 0$ for at least one i

Research Objective 3:

Null Hypothesis (H_0): Deployment of Lean Six Sigma process improvement initiatives will not improve the financial status of hospitals to alleviate and prevent the closure risk of hospitals.

Alternative Hypothesis (H_1): Deployment of Lean Six Sigma process improvement initiatives will improve financial status of hospitals to alleviate and prevent the closure risk of hospitals.

Chapter 4

Analysis/Results

4.1 Statistical Analysis for Predicting Closures

Overview

The objective of the research objective 2 is to evaluate the factors that may cause the risk of rural hospital closures. From 2012-2016, 63 rural hospitals have closed around the country that have been used for statistical analysis purposes. Although the hospital closures continue until this point of time (October 2016), the cutoff was set by early 2016 (March). For logistic regression modeling purposes, 400 open hospitals are considered to be compared with the closed hospitals.

Table 4.1: Closed and Open Hospitals Data

Closed Hospital (Total)	**63**
Open Hospital (Total)	400
Training Data (Closed)	55
Training Data (Open)	315
Testing Data (Closed)	8
Testing Data (Open)	85

The data was segregated in to two groups, tagged as “training” and “testing” data sets in which the training data set will contain 80% of the total data and testing data set will contain 20% of the data. While the training data set was used for model formation purposes, the testing data set was used for model validation purposes.

4.1.1 Missing Value Analysis:

When data was collected for the model variables, data was not available for some hospitals. Appropriately handling missing values is critical for building the model and making conclusions from it. Here, missing values are replaced by hospital closure percentage based imputation.

Table 4.2: Sample Calculation Table for Missing Values (Pneumonia Readmission)

Group	Min	Max	Average	No. of Closed	Closed %	No. of Open	Open %	Total	Percent Total
1			18.94	14	48.3%	15	51.72%	29	6.26%
2	14.3	16.9	16.24	3	3.75%	77	96.25%	80	17.30%
3	17	17.6	17.31	8	8.7%	84	91.3%	92	19.9%
4	17.7	18.4	18.08	10	11.8%	75	88.24%	85	18.40%
5	18.5	19.5	18.94	18	20.00%	72	80.00%	90	19.40%
6	19.6	24.2	20.70	10	11.5%	77	88.51%	87	18.80%

For closure percentage based imputation, the data set has been divided into groups or bins including a separate group for missing values. Then the hospital closure percentage for the missing value group is compared with the other groups. The missing values are replaced by the average value of a group which has the closure percentage closest to that of the missing value group's closure percentage. From the sample missing value table above for Pneumonia Readmission, about 6% of the hospitals have missing data for the Pneumonia readmission variable and hence the variable data has been divided in to groups in order to impute missing values. From the table, the closure percentage of missing value group (group 1) is 48.3% and the closest closure percentage from other groups here is 20% from group 5. Hence the average value of 18.94 from group 5, is replaced as the missing values for group 1.

4.1.2 Descriptive Statistics Analysis:

4.1.2.a PN_3B Measure (Blood culture performed in the Emergency Department prior to initial Antibiotic received in hospital).

The median percentage of PN_3B process compliance for closed hospitals is 82%. The spread of values is considerably large ranging from 60% up to 100% which may indicate some lapses in care compliance for this process measure among closed hospitals. Also, most of the closed hospitals have compliance rate around 82% denotes that many hospitals are not fully compliant with the measure. The distribution of the data from the histogram indicates that the data is clearly not normal.

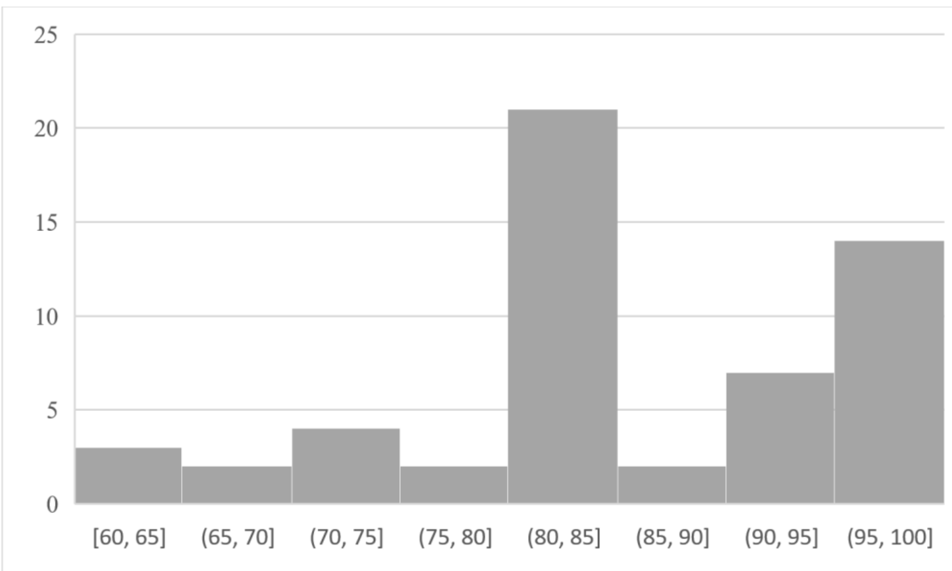


Figure 4.1: Histogram for PN_3B Process Measure

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

PN_3B Process measure will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

PN_3B Process measure will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005

Results:

	N	Mean Score
PN_3B_O	315	198.155556
PN_3B_C	55	113.018182

Normal Approximation	
Z	-5.4893
One-Sided Pr < Z	<.0001
Two-Sided Pr > |Z|	<.0001

Average Scores used for ties

Conclusion:

At $p < 0.0001$, there is an evidence of association between PN_3B process measure and closure of hospitals, i.e., PN_3B process measure affects closure of hospitals.

PN_3B Vs Logit Analysis

A different form of bivariate analysis is to plot the independent variables against the raw logits which is commonly used in logistic regression. It is performed to understand the independent variable (IV) and dependent variable (DV) relationships and provides meaningful information on the associations which can be used later in the logit model. By graphing the logits of closure against the independent variable, The IV and DV relationship is analyzed by the direction and form of association between the likelihood of closure and IV. It is done by grouping each independent variable into bins (ranking the observations) and corresponding mean for each bin is calculated. The raw Logits are then plotted against the means for each bin.

The plot for PN_3B Vs. the raw logits displays a downtrend negative trend, although not much linear, still exhibiting an association such that as the percentage of compliance with PN_3B process increases, the likelihood of closure decreases, which indicates that the variable may contribute to the model. The increase in PN_3B process compliance will likely reduce the financial pressures for hospitals by avoiding reimbursement cuts and create revenue opportunities by bringing incentives for performing well on this measure.

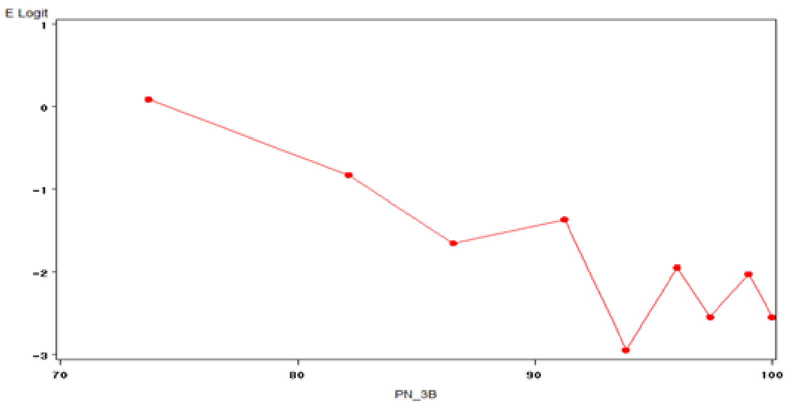


Figure 4.2: Trend Analysis for PN_3B Measure

4.1.2.b PN_6 Measure (Initial antibiotic selection for Community-Acquired Pneumonia in Immunocompetent patients)

This variable denotes the compliance measure for pneumonia condition. As the compliance rate of this measure increases, the risk of hospital closures decreases. The distribution of data shows that the data is not normal. The closures occurred for hospitals with a compliance range between 36% to 100% but the hospitals with a compliance percentage of about 72% experienced most closures, which also indicates that many closed hospitals are not fully compliant with this process measure.

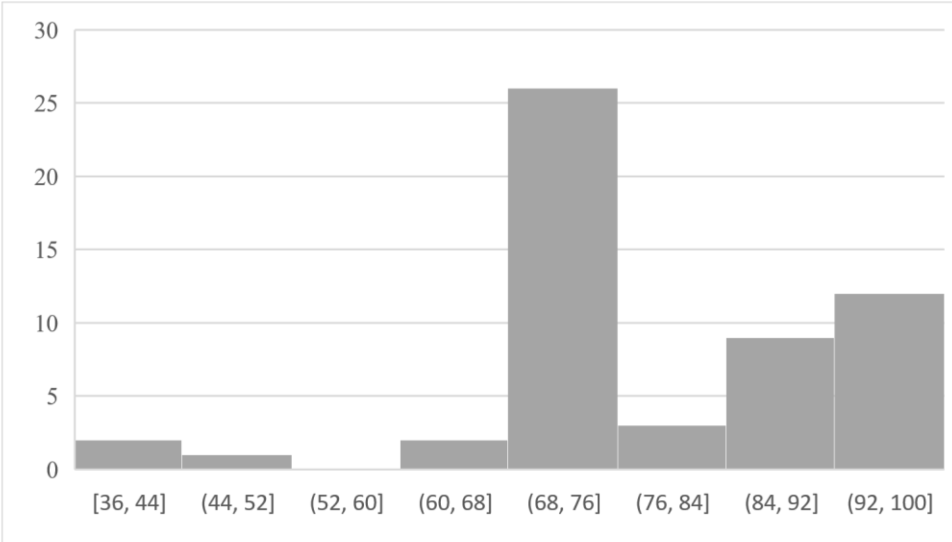


Figure 4.3: Histogram for PN_6 Process Measure

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

PN_6 Process measure will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

PN_6 Process measure will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005

Results:

	N	Mean Score
PN_6_O	315	198.392063
PN_6_C	55	111.663636

Normal Approximation	
Z	-5.5651
One-Sided Pr < Z	<.0001
Two-Sided Pr > |Z|	<.0001

Average Scores used for ties

Conclusion:

At $p < 0.0001$, there is an evidence of association between PN_6 process measure and closure of hospitals, i.e., PN_6 process measure affects closure of hospitals.

PN_6 Vs logit Analysis:

The graphical analysis of the PN_6 variable and the logits shows an overall downtrend which indicates the association of PN_6 and closure of hospitals. As the percentage of compliance with the PN_6 process measure increases, the likelihood of closure decreases.

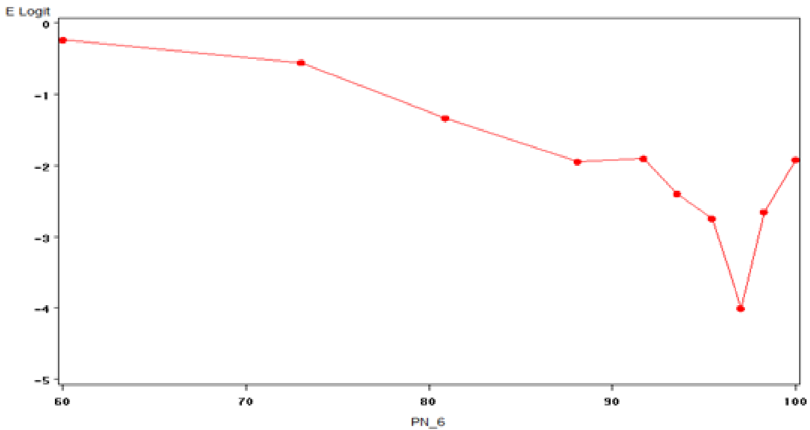


Figure 4.4: Trend Analysis for PN_6 Process Measure

4.1.2.c Heart Failure Readmission:

The closed hospitals' readmission rates for heart failure condition have a relatively small range of 9.3% with many closed hospitals having the median readmissions rate of 27%. The distribution of the Heart failure readmission data is clearly not normal from the histogram.

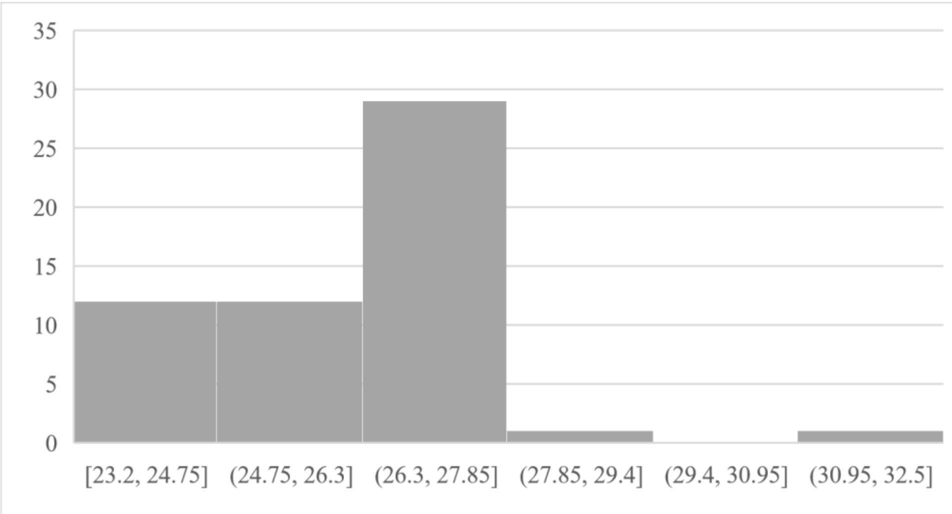


Figure 4.5: Histogram for Heart Failure Readmission Process Measure

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

Heart Failure Readmission Process measure will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

Heart Failure Process measure will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005

Result

	N	Mean Score
HF_Readmission_O	315	173.168254
HF_Readmission_C	55	256.127273

Normal Approximation	
Z	5.3115
One-Sided Pr > Z	<.0001
Two-Sided Pr > |Z|	<.0001

Average Scores used for ties

Conclusion:

At $p < 0.0001$, there is an evidence of association between Heart Failure Readmission process measure and closure of hospitals, i.e., Heart Failure Readmission process measure affects closure of hospitals.

Heart Failure Readmission Vs Logit Analysis:

From the logit Vs. Heart Failure Readmission plot, a positive upward trend is observed, although not completely linear, which indicate that as the Heart Failure Readmission level increases, the odds of closure increase as well which informs that this variable may contribute to the model. Hospitals with high percentage of readmissions than the national average will be penalized and hence will cause financial problems for hospitals. Hence, as the rate of readmissions increases, the likelihood of closure also increases.

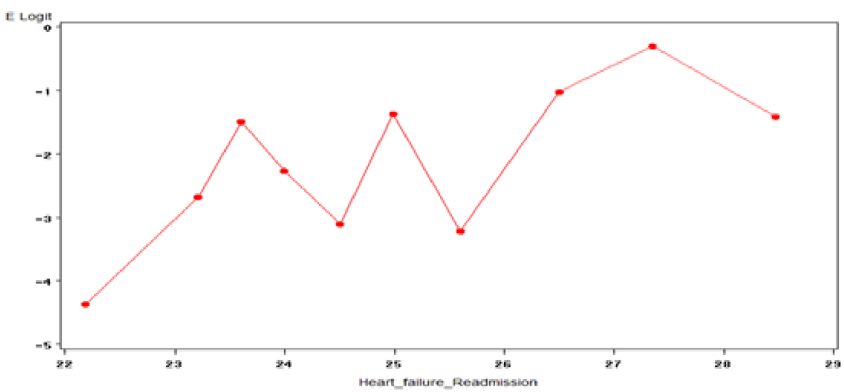


Figure 4.6: Trend Analysis for Heart Failure Readmission Process Measure

4.1.2.d Number of Hospitals

By looking at the distribution, the data is clearly not normal. The number of hospitals present in the same county as closed hospitals range from a minimum of 1 to maximum of 7, with the closed hospitals having nearby hospitals of up to 2 experienced the most number of closures.

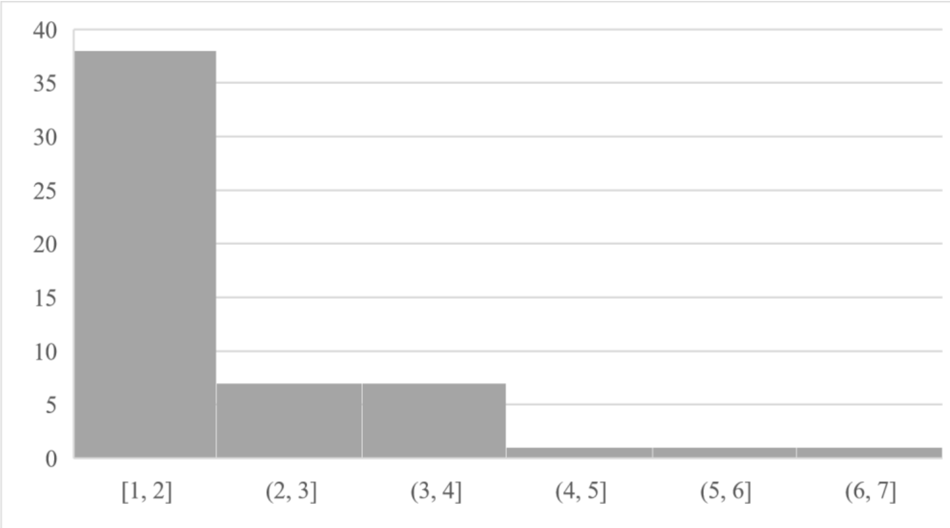


Figure 4.7: Histogram for Number of Hospitals

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

Number of Hospitals will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

Number of Hospitals will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005

Results:

	N	Mean Score
No. of Hospitals_O	315	177.677778
No. of Hospitals_C	55	230.300000

Normal Approximation	
Z	3.8821
One-Sided Pr > Z	<.0001
Two-Sided Pr > |Z|	<0.0001

Average Scores used for ties

Conclusion:

At $p < 0.0001$, there is an evidence of association between Number of Hospitals and closure of hospitals, i.e., Number of Hospitals affects closure of hospitals

Number of Hospitals Vs. Logit Analysis

The logit plotted against the number of hospitals variables displays an almost straight positive trend such that as the number of hospitals increases, the odds of closure increases. This is true to large extent since as more number of hospitals are present in a given area, the competition among hospitals increases, and hence more likely, the hospitals lose revenue.

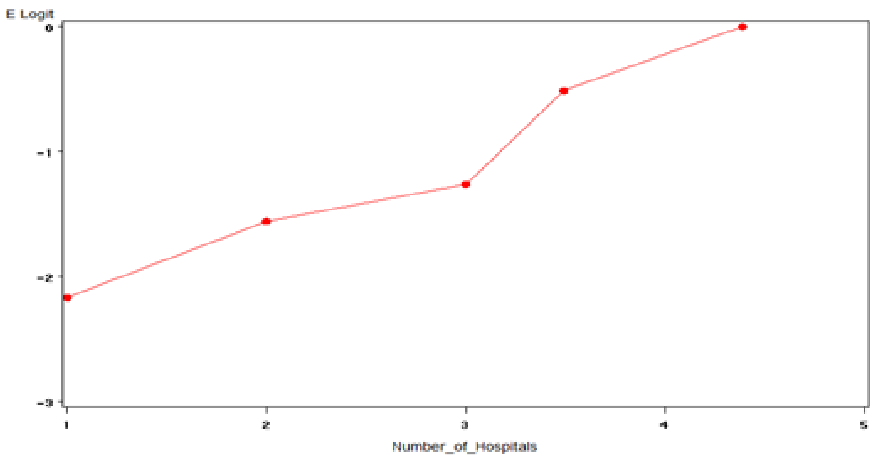


Figure 4.8: Trend Analysis for Number of Hospitals

4.1.2.e Hispanic Population

From the data distribution for Hispanic population living near closed hospitals, it looks like the data is heavily skewed to the right. The calculated range for the Hispanic population data is 39262 with a median value of 1444. The By only looking at the above two parameters, it suggests that the data is widely spread, but many closed hospitals had the population of up to 7165 living nearby.

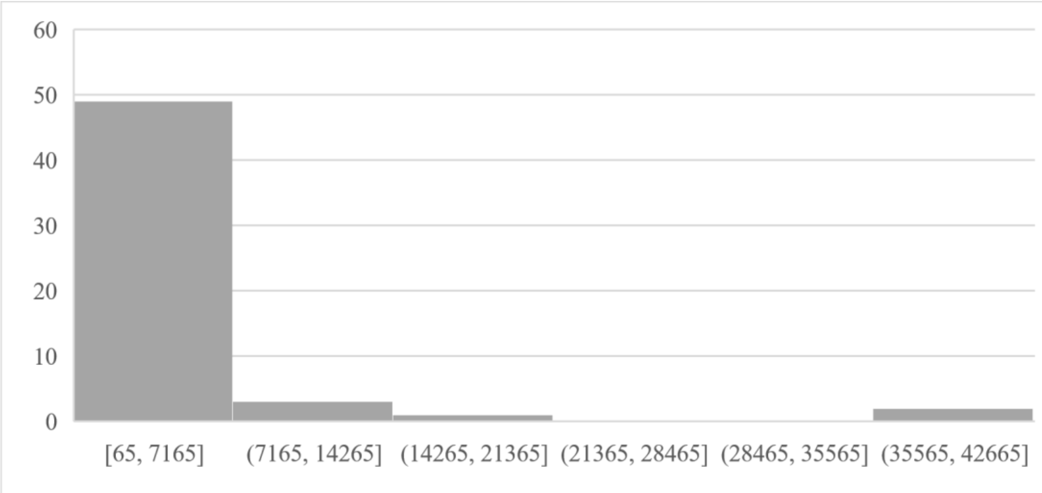


Figure 4.9: Histogram for Hispanic Population

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

Hispanic Population will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

Hispanic Population will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005.

Results:

	N	Mean Score
Hispanic_Population_O	315	183.388889
Hispanic_Population_C	55	197.590909

Normal Approximation	
Z	0.9080
One-Sided Pr > Z	0.1820
Two-Sided Pr > |Z|	0.3639

Average Scores used for ties

Conclusion:

At p = .3639, there is no evidence of association between Hispanic Population and closure of hospitals, i.e., Hispanic Population will not affect closure of hospitals.

Hispanic Population Vs. Logit Analysis

The logit Vs. Hispanic population does not show any positive or negative relationship, but it does show that the data points are clustered with many data points at the beginning which is an indication of some skewness present in the overall distribution of closed and open hospitals. The absence of the trend suggests that there may not be any relationship between the independent and the dependent variable and the variable will not contribute to the model.

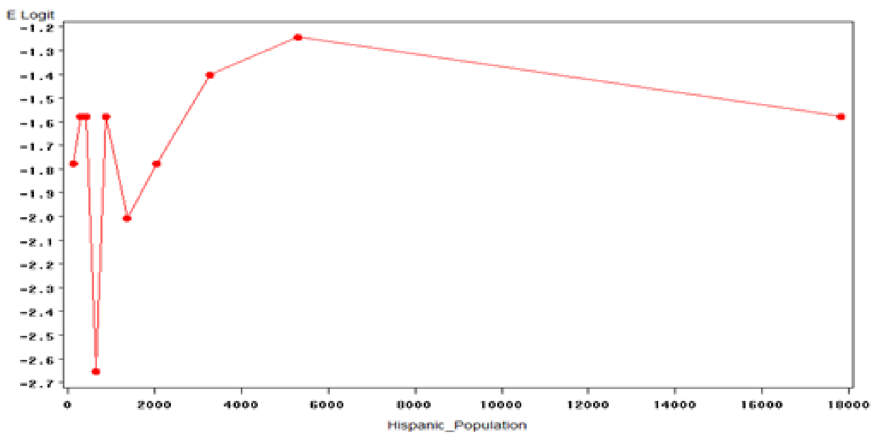


Figure 4.10: Trend Analysis for Hispanic Population

4.1.2.f Disadvantaged Population

The disadvantaged population residing near the close hospitals range from 46 to 22293 in which, closed hospitals having a population strength of up to 4446 living nearby experienced maximum number of closures. Also, by looking at the above distribution, the data is clearly not normal and indicates some skewness might be present.

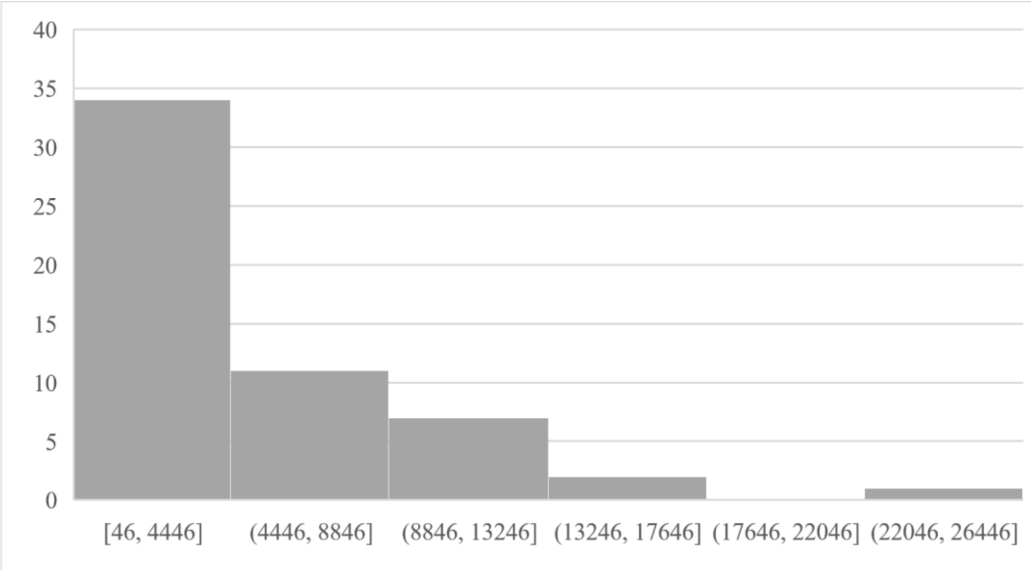


Figure 4.11: Histogram for Disadvantaged Population

Mann-Whitney-Wilcoxon Test

Test Hypothesis:

H_0: Population distribution of closed hospital group = Population distribution of open hospital group

Disadvantaged Population will not affect hospital closure status

H_1: Population distribution of closed hospital group ≠ Population distribution of open hospital group

Disadvantaged Population will affect hospital closure status

Rejection Criteria: At 0.05 significance level, reject null hypothesis if p-value is <0.005 and fail to reject null hypothesis if p-value is >0.005

Results:

	N	Mean Score
Disadvantaged_Population_O	315	175.726984
DisadvantagedPopulation_C	55	241.472727

Normal Approximation	
Z	4.2071
One-Sided Pr > Z	<.0001
Two-Sided Pr > |Z|	<.0001

Average Scores used for ties

Conclusion:

At $p < 0.0001$, there is an evidence of association between Disadvantaged Population and closure of hospitals, i.e., Disadvantaged Population affects closure of hospitals

Disadvantaged Population Vs. Logit Analysis

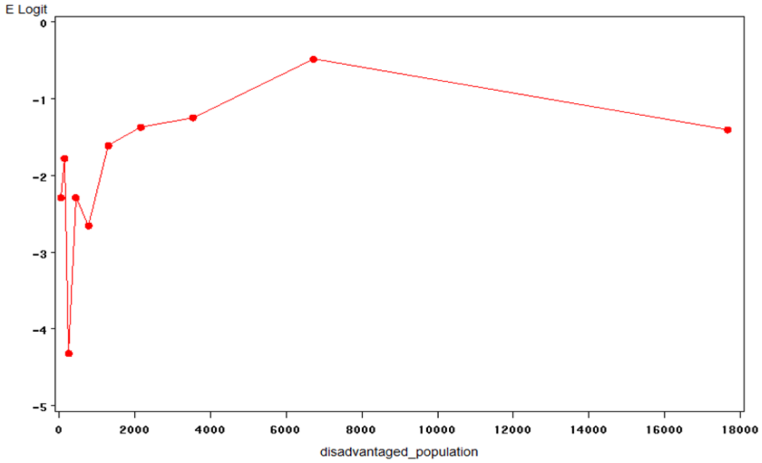


Figure 4.12: Trend Analysis for Disadvantaged Population

The logits Vs. Disadvantaged population does not show any clear trend present. But it is evident from the distribution that there may be some skewness present at the beginning.

4.1.3 Categorical Classification of Continuous Predictor Variables

The overall data distribution of Disadvantaged Population and Hispanic Population for open and closed hospitals are highly skewed to the right, i.e., positively skewed. The calculated skewness for Disadvantaged Population and Hispanic Population are 3.93 & 3.85, the standard errors are 307.88 & 309.36 and median values are 983 & 1071 respectively. The relatively larger values of skewness and standard error suggests that it would lead to biased results. For variables of this high skewness and standard error, the continuous data can be converted to categorized ones to better understand the data. Hence a categorical variable is created using the median value for both the variables. The table below shows the data for Hispanic and disadvantaged population are categorized such as one data group is less than 1000 and another group is greater than or equal to 1000.

Table 4.3: Categorical Classification of Continuous Predictor Variables

Disadvantaged Population	Hispanic Population
Disadvantaged Population_1 < 1000	Hispanic Population_1 < 1000
Disadvantaged Population_2>=1000	Hispanic Population_2>=1000

For modeling purposes, the categorized variables will be used. However, a model created using raw data will be compared with the model using categorized variables for comparison and evaluation purposes.

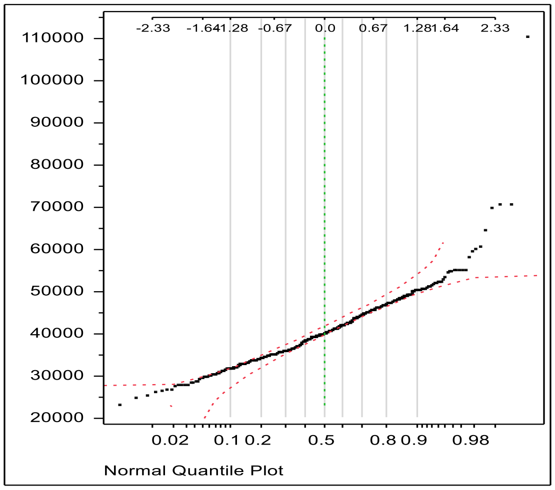
4.1.4 Log transformation of Continuous Predictor Variables:

Although the skewness for population estimate and median household income was not relatively very high (2.68 and 1.98 respectively), the standard errors were very high (435.94 and 1901.28 respectively). A log transformation will help to reduce the standard error as well as the skewness, which in turn will help to improve the predictive ability of the median household income and population estimate variables on the dependent variable.

The table below shows the results of skewness and standard error after completing log transformation. As evident, the standard error as well as the skewness has considerably been reduced. The normality plots for Median Household Income and Population Estimate also shows the before and after scenarios of log transformation of the two variables which depicts improved normality. The above log transformed variables will be used for modeling purposes.

Table 4.4: Log transformed Results for Continuous Predictor Variables

Variable	Standard Error	Skewness
Median Household Income_L	0.01	0.4
Population Estimate_L	0.04	-0.42



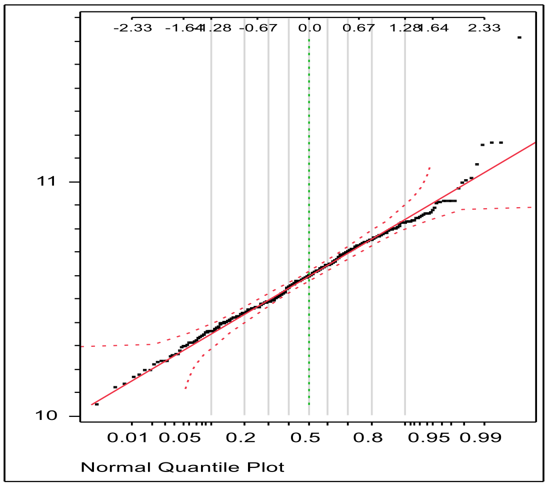
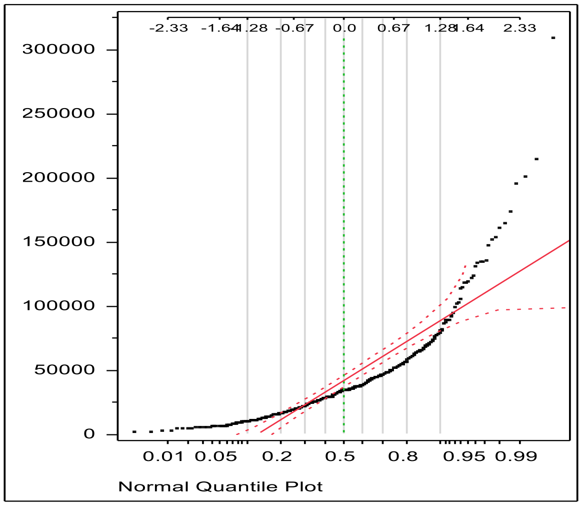


Figure 4.13: Normal Quantile Plot for Median Household Income before and after log transformation



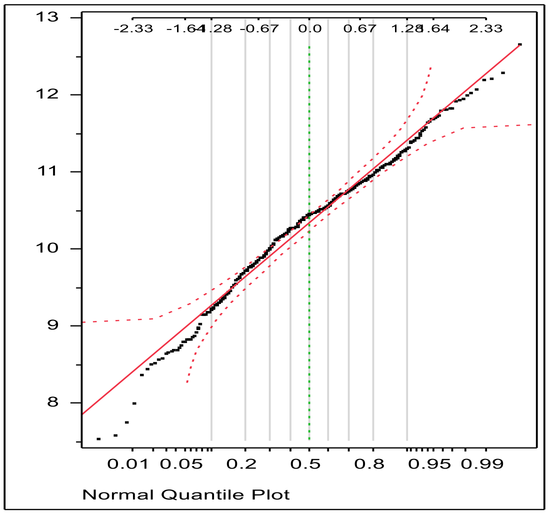


Figure 4.14: Normal Quantile Plot for Population Estimate before and after log transformation

4.1.5 Correlation Analysis:

The correlation analysis is performed to quantify the strength of any linear relationship between the independent variables. The matrix plot below shows a positive correlation among the three variables-No Patient Recommendation & No Immediate help, No Patient Recommendation & No Nurse Communication and No Immediate Help & No Nurse Communication.

	No patient recommendation	No Immediate help
No Immediate help	r= 0.816	
	p= 0.000	
No Nurse Communication	r= 0.880	r= 0.865
	p= 0.000	p= 0.000

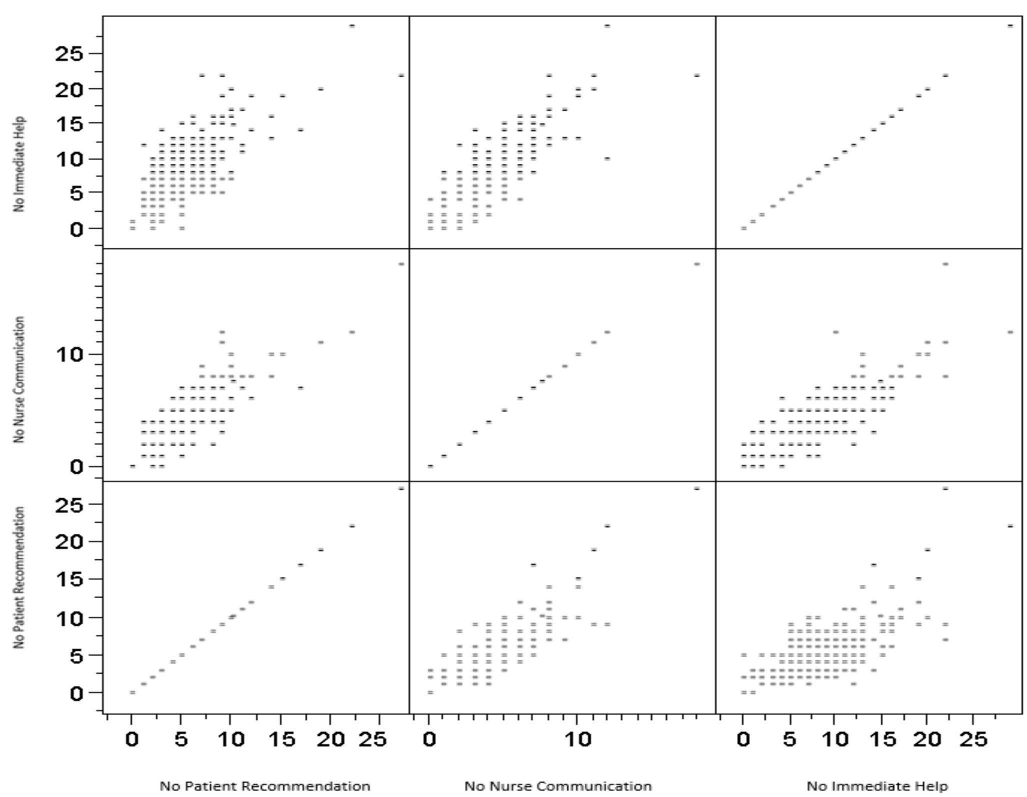


Figure 4.15: Correlation Matrix for Continuous Predictors

The results from the correlation analysis above shows that the correlation between No Patient Recommendation & No Immediate Help is 0.816, No Patient Recommendation & No Nurse Communication is 0.880 and No Nurse Communication & No Immediate Help is 0.860.

A positive higher correlation value closer to 1 indicates that there is a strong relationship exists between two independent variables such that when there is an increase in value of one variable, the value of the other variable increases as well. The correlation values of 0.816, .880 and .865 indicates that the variables are related fairly strongly with each other. The corresponding p values are all less than 0.05 which indicates that the correlations are significant.

Multicollinearity could be a potential issue due to high correlations between No Patient Recommendation, No Immediate Help and No Nurse Communication. Presence of multicollinearity may affect the model performance.

Running regression models with potentially correlated variables may confirm the presence of multicollinearity. A Variation Inflation Factor value of >5 will indicate the presence of multicollinearity.

In the following sections, a series of models was run with all possible combinations of potential correlated variables to check for multicollinearity problem.

Multicollinearity Check Model 1:

Variable	DF	Parameter Estimate	Standard Error	Pr > |t|	Variance Inflation
Intercept	1	0.02029	0.04110	0.6218	0
No Patient Recommendation	1	0.02993	0.01089	0.0063	4.69098
No Nurse Communication	1	-0.04526	0.01802	0.0125	6.21364
No Immediate Help	1	0.01737	0.00780	0.0266	4.19253

The results from above model shows the VIF value for No Nurse Communication variable is >5 and other two variables, No Patient Recommendation and No Immediate Help have VIF value is < 5. Looking at this model shows that multicollinearity will have influence in the model in the presence of No Nurse Communication variable. Further, in the correlation analysis, the highest correlated value is .880 between No Nurse Communication and No Patient Recommendation.

Multicollinearity Check Model 2:

Variable	DF	Parameter Estimate	Standard Error	Pr > |t|	Variance Inflation
Intercept	1	0.04873	0.03927	0.2155	0
No Patient Recommendation	1	0.03552	0.01065	0.0009	4.44143
No Nurse Communication	1	-0.02384	0.01532	0.1205	4.44143

The VIF values for No Patient Recommendation and No Nurse Communication are 4.44143 which is <5, and hence multicollinearity will not be a problem with the presence of the above two variables in the model.

Multicollinearity Check Model 3:

Variable	DF	Parameter Estimate	Standard Error	Pr > |t|	Variance Inflation
Intercept	1	0.01107	0.04133	0.7890	0
No Nurse Communication	1	-0.01549	0.01453	0.2872	3.96950
No Immediate Help	1	0.02232	0.00766	0.0038	3.96950

The VIF values for No Nurse Communication and No Immediate help are <5 and hence multicollinearity will not be an issue with the presence of the above two variables.

Multicollinearity Check Model 4:

Variable	DF	Parameter Estimate	Standard Error	Pr > |t|	Variance Inflation
Intercept	1	0.00171	0.04072	0.9665	0
No Patient Recommendation	1	0.01350	0.00876	0.1244	2.99677
No Immediate Help	1	0.00690	0.00665	0.2996	2.99677

The VIF values of No Patient Recommendation and No Immediate Help are <5 (2.99677), which are the least VIF values among other trials for multicollinearity check. Also, the correlation analysis performed on the above variables resulted in .816, which is again the least among the all. Multicollinearity will not be an issue with the presence of above two variables.

From the correlation analysis and multicollinearity check using the VIF values, the variable No Nurse Communication seems to cause multicollinearity problems and hence will be removed from the model.

4.1.6 Model Formation

In the following sections, three models are created. The first and the second model are created using the financial importance and operational importance independent variables discussed in the methodology section. The third model is created using the significant predictors from models 1 and 2 for predicting closures. A binary logistic regression method is used for predicting hospital closures and hence a binary dependent variable., 1-Closed, 0-Open is used. Also, for variable selection, backward selection procedure is used for all three models.

4.1.6.1 Financial Importance Model (Model 1)

To begin with model 1, the following independent variables are selected for analysis.

Number of Hospitals

Percent Uninsured

Median Household Income_L

Population Estimate_L,

Disadvantage population_2,

Hispanic Population_2

Begin backward selection procedure for model 1:

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	263.798
SC	316.978	291.193
-2 Log L	311.065	249.798

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	61.2665	6	<.0001
Score	58.9224	6	<.0001
Wald	44.6712	6	<.0001

Step 1: Effect Hispanic_Population_2 is removed.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	262.703
SC	316.978	286.185
-2 Log L	311.065	250.703

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	60.3613	5	<.0001
Score	58.2898	5	<.0001
Wald	44.0156	5	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.9039	1	0.3417

Step 2: Effect Median Household Income_L is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	264.393
SC	316.978	283.960
-2 Log L	311.065	254.393

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	56.6719	4	<.0001
Score	55.7189	4	<.0001
Wald	42.0130	4	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
4.5212	2	0.1043

Note: No additional effects met the 0.05 significance level for removal from the model

Summary of Backward Elimination					
Step	Effect Removed	DF	Number In	Wald Chi-Square	Pr > ChiSq
1	Hispanic_Population_2	1	5	0.8995	0.3429
2	Median Household Income_L	1	4	3.5579	0.0593

Table 4.5: Analysis of Maximum Likelihood of Estimates results for Model 1

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	2.0667	2.4028	0.7398	0.3897
Number of Hospitals	1	1.0191	0.1913	28.3871	<.0001
Percent Uninsured	1	0.0934	0.0375	6.2026	0.0128
Population Estimate_L	1	-0.8064	0.2406	11.2334	0.0008
Disadvantaged Population_2	1	1.5406	0.3875	15.8069	<.0001

Table 4.6: Odds Ratio Estimates results for Model 1

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Number of Hospitals	2.771	1.905	4.031
Percent Uninsured	1.098	1.020	1.182
Population Estimate_L	0.446	0.279	0.715
Disadvantaged Population_2	4.667	2.184	9.974

Table 4.7: Association of Predicted Probabilities and Observed Responses results for Model 1

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	80.6	Somers' D	0.616
Percent Discordant	19.0	Gamma	0.618
Percent Tied	0.3	Tau-a	0.156
Pairs	17325	c	0.808

Table 4.8: Hosmer and Lemeshow Goodness-of-Fit Test results for Model 1

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
14.3560	8	0.0729

--END OF MODEL 1--

From mode1 1 results, at 95% confidence level, variables Number of Hospitals, Percent Uninsured Population Estimate_L and Disadvantaged Population_2 are significant ($p<0.05$). These variables will be used in the combined model along with the significant variables from Operational importance model to create model 3 for predicting closures.

The goodness of fit test (Hosmer and Lemeshow) results with $p > 0.05$, which shows that the model is acceptable and the model adequately fit the data.

Table below summarizes the significant predictors which causes hospital closures that are external to the hospital i.e., factors that are externally present outside the hospital to affect closures.
By looking at this financial importance model alone and analyzing the odds ratio estimates, we will have some crucial information for the financial importance model.

From the odds ratio analysis,

The odds ratio for number of hospitals is 2.771. In percentage terms, an increase of one hospital in a county increases the odds of closure by 177%.

The odds ratio for percent uninsured is 1.098. In percentage terms, an increase of 1% uninsured population in a county increases the odds of closure by 9.8%.

The odds of closure of hospitals in disadvantaged_population_2 locality over the odds of closure of hospitals in disadvantaged_population_1 locality are 4.667. It means hospitals in disadvantaged locations where population is greater than or equal to 1000 are more likely to be closed in comparison with hospitals in disadvantaged locations where population is less than 1000. In percentage terms, odds of closure of hospitals in disadvantaged_population_2 locality is 367% higher than hospitals in disadvantaged_population_1 area.

The odds ratio for population estimate of .446 indicates that an unit increase in population decreases the risk of closure by 55.4%.

Table 4.9: Summary of Significant Predictors for Financial Importance Model

Variable	Coefficient	Wald Chi-Square
Number of Hospitals	1.0191	28.3871
Percent Uninsured	0.0934	6.2026
Disadvantaged Population_2	1.5406	15.8069
Population Estimate	-.8064	11.2234

4.1.6.1.a Model 1 check without transformation and categorical classification

In order to evaluate model 1 without log transformation of Median Household Income & Population estimate variables as well as creating categorical classification for Disadvantaged Population and Hispanic Population variables, a model analysis is performed only using the raw data. The following are the analysis results as shown.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.7722	1.4106	1.5784	0.2090
Number of Hospitals	1	0.8686	0.1599	29.4976	<.0001
Percent Uninsured	1	0.0914	0.0379	5.8176	0.0159
Median Household Income	1	-0.00008	0.000027	9.3188	0.0023

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Number of Hospitals	2.384	1.742	3.261
Percent Uninsured	1.096	1.017	1.180
Median Household Income	1.000	1.000	1.000

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	79.9	Somers' D	0.603
Percent Discordant	19.7	Gamma	0.605
Percent Tied	0.4	Tau-a	0.153
Pairs	17325	c	0.801

From the above analysis, it can noted that the results are different compared to the analysis results that was done using transformation and creating categorical classification of variables. At 95% confidence level, there are three predictors which are significant ($p<0.05$). among them, predictor Median Household Income will not make much contribution to the model since the coefficient is almost zero and the resulting odds ratio of 1 suggests that the variable neither predict closure nor non-closure of hospitals. Also, the percent concordant and the Somer's D value which indicates the accuracy of the model is relatively less compared to the model using transformed and categorized variables. Effectively, only two variables, Number of Hospitals and Percent Uninsured predicts hospital closure using raw data for model 1 in comparison with 4 variables that can predict closures for model 1 formed using transformed and categorized variables. Thus, the preferred model using transformed Median Household Income & Population Estimate variables as well as categorized Hispanic and Disadvantaged Population variables prove to be better to form model 1 in comparison to forming the model only using the raw data.

4.1.6.1.b Model 1 check with variables categorized Vs. Log transformation

To reduce high standard error as well to reduce skewness for Disadvantaged Population and Hispanic Population variables, the other option is to do a log transformation of those variables. Although creating categorical variables has resulted in better results in comparison to forming model using raw data, a model created using log transformed Hispanic and Disadvantaged Population variables can be compared with that of the categorized ones to choose the better alternative. The following analysis results shows Model 1 using log transformed Disadvantaged Population and Hispanic Population variables.

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	2.0498	2.4369	0.7075	0.4003
Number of Hospitals	1	1.0445	0.1923	29.5040	<.0001
Percent Uninsured	1	0.0779	0.0384	4.1153	0.0425
Population Estimate_L	1	-0.9802	0.2650	13.6827	0.0002
Disadvantaged_Population_L	1	0.4191	0.1106	14.3533	0.0002

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	80.1	Somers' D	0.605
Percent Discordant	19.5	Gamma	0.608
Percent Tied	0.4	Tau-a	0.154
Pairs	17325	c	0.803

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Number of Hospitals	2.842	1.950	4.143
Percent Uninsured	1.081	1.003	1.165
Population Estimate_L	0.375	0.223	0.631
Disadvantaged Population_L	1.521	1.224	1.889

From the above analysis, in comparison with the original preferred model using categorization of Disadvantaged and Hispanic Population variables, the predictors remain the same for Model 1. Also from the analysis, although the percent concordant does not vary much from the original preferred model with a difference of 0.5, there is a difference in Somer's D value of 1.1, which suggests categorization of Hispanic and Disadvantaged population is a better option in comparison with log transformation of the two variables.

4.1.6.2 OPERATIONAL IMPORTANCE MODEL (Model 2)

To begin with model 2, the following independent variables are selected for analysis.

Intercept, Pneumonia Readmission, Heart Failure Readmission, No Patient Recommendation, No Pain Management, Blood Infection, No Doctor Communication, Pneumonia Mortality, PN_3B, PN_6, HF_1, No Medication Instructions, No Post Discharge Info, No Immediate help.

The dependent variable is a binary variable., 1-Closed, 0-Open. As mentioned earlier, backward elimination procedure is used for variable selection.

Begin backward selection Procedure for Model 2:

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	267.604
SC	316.978	318.480
-2 Log L	311.065	241.604

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.4627	13	<.0001
Score	73.3234	13	<.0001
Wald	50.8580	13	<.0001

Step 1: Effect No Doctor Communication is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	265.625
SC	316.978	312.587
-2 Log L	311.065	241.625

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.4606	12	<.0001
Score	73.3220	12	<.0001
Wald	50.9134	12	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.0022	1	0.9630

Step 2: Effect No Patient Recommendation is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	269.602
SC	316.978	324.391
-2 Log L	311.065	241.602

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.4395	11	<.0001
Score	73.2913	11	<.0001
Wald	51.0508	11	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.0231	2	0.9885

Step 3: Effect No Post Discharge info is removed.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	263.653
SC	316.978	306.701
-2 Log L	311.065	241.653

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.4121	10	<.0001
Score	73.2878	10	<.0001
Wald	51.0637	10	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.0507	3	0.9970

Step 4: Effect HF_1 is removed.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	261.686
SC	316.978	300.821
-2 Log L	311.065	241.686

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.3787	9	<.0001
Score	73.1031	9	<.0001
Wald	51.0269	9	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.0841	4	0.9991

Step 5: Effect Pneumonia Mortality is removed.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	259.946
SC	316.978	295.167
-2 Log L	311.065	241.946

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	69.1190	8	<.0001
Score	72.4408	8	<.0001
Wald	50.3679	8	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.3408	5	0.9968

Step 6: Effect No Immediate Help is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	258.237
SC	316.978	289.545
-2 Log L	311.065	242.237

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	68.8278	7	<.0001
Score	72.0345	7	<.0001
Wald	50.5920	7	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
.6195	6	.9961

Step 7: Effect Blood Infection is removed.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	256.979
SC	316.978	284.374
-2 Log L	311.065	242.979

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	68.0857	6	<.0001
Score	71.9088	6	<.0001
Wald	50.7251	6	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
1.2539	7	.9896

Step 8: Effect No Medication Instructions is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	256.253
SC	316.978	279.734
-2 Log L	311.065	244.253

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	66.8117	5	<.0001
Score	70.6248	5	<.0001
Wald	51.0656	5	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
2.4613	8	0.9635

Step 9: Effect Pneumonia Readmission is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	256.020
SC	316.978	275.587
-2 Log L	311.065	246.020

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	65.0452	4	<.0001
Score	69.1947	4	<.0001
Wald	50.7083	4	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
4.2310	9	0.8956

Step 10: Effect No Pain Management is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	257.014
SC	316.978	272.668
-2 Log L	311.065	249.014

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	62.0509	3	<.0001
Score	66.4705	3	<.0001
Wald	49.8094	3	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
7.1506	10	0.7112

Note: No Additional effects met the 0.05 significance level for removal from the model

Step	Effect Removed	DF	Number In	Wald Chi-Square	Pr > ChiSq
1	No Doctor Communication	1	12	0.0022	0.9630
2	No Patient Recommendation	1	11	0.0210	0.8847
3	No Post Discharge Info	1	10	0.0276	0.8682
4	HF_1	1	9	0.0335	0.8547
5	Pneumonia Mortality	1	8	0.2567	0.6124
6	No Immediate Help	1	7	0.2870	0.5922
7	Blood Infection	1	6	0.6050	0.4367
8	No Medication Instructions	1	5	1.2738	0.2591
9	Pneumonia Readmission	1	4	1.7782	0.1824
10	No Pain Management	1	3	2.9216	0.0874

Table 4.10: Analysis of Maximum Likelihood of Estimates results for Model 2

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-1.8583	3.1837	0.3407	0.5594
Heart Failure Readmission	1	0.3407	0.0934	13.3002	0.0003
PN_3B	1	-0.0640	0.0235	7.4492	0.0063
PN_6	1	-0.0331	0.0162	4.1700	0.0411

Table 4.11: Odds Ratio Estimates results for Model 2

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Heart Failure Readmission	1.406	1.171	1.688
PN_3B	0.938	0.896	0.982
PN_6	0.967	0.937	0.999

Table 4.12: Association of Predicted Probabilities and Observed Responses results for Model 2

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	77.7	Somers' D	0.572
Percent Discordant	20.5	Gamma	0.582
Percent Tied	1.8	Tau-a	0.145
Pairs	17325	c	0.786

Table 4.13: Hosmer and Lemeshow Goodness-of-fit Test results for Model 2

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
6.2737	8	0.6166

--END OF MODEL 2--

At 95% confidence level, variables Heart_Failure_Readmission, PN_3B and PN_6 are significant. These variables will be used along with the significant variables from the financial importance model to create the final model for predicting hospital closures.

The goodness of fit test (Hosmer and Lemeshow) results show that the model is acceptable (p>0.05) and the model adequately describe the data.

Odds Ratio Estimates Evaluation

The odds ratio for Heart Failure Readmission is 1.046. In percentage terms, an one percent increase Heart Failure Readmission will increase the odds of closure by 4.6%.

The odds ratio for PN_6 is .938. An one percent increase in PN_6 compliance reduces the odds of closure by 6.2%

The odds ratio for PN_3B is 0.967. An one percent increase in PN_3B compliance reduces the odds of closure by 3.3%

Table 4.14: Summary of Significant Predictors for Operational Importance Model

Variable	Coefficient	Wald Chi-Square
PN_3B	-0.0640	7.4492
Heart Failure Readmission	0.3407	13.3002
PN_6	-0.0331	4.170

4.1.6.3 Final Model- Combination of Financial and Operational Importance Models (Model 3)

For model 3, as mentioned earlier, the following significant predictors from models 1 and 2 are used as shown below.

Heart Failure Readmission

PN_6

PN_3B

Number of Hospitals

Percent Uninsured

Population Estimate_L

Disadvantaged Population_2

The dependent variable is a binary variable 1-Closed, 0-Open. Similar to models 1 and 2, backward selection procedure is used for variable selection.

Begin Backward Selection Procedure for Model 3:

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	222.557
SC	316.978	253.865
-2 Log L	311.065	206.557

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	104.5077	7	<.0001
Score	102.9263	7	<.0001
Wald	59.8501	7	<.0001

Step 1: Effect Population Estimate Log is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	220.651
SC	316.978	248.045
-2 Log L	311.065	206.651

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	104.4142	6	<.0001
Score	102.8075	6	<.0001
Wald	59.8243	6	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.0939	1	0.7593

Step 2: Effect Percent Uninsured is removed

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	313.065	219.200
SC	316.978	242.681
-2 Log L	311.065	207.200

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	103.8653	5	<.0001
Score	102.6700	5	<.0001
Wald	59.3377	5	<.0001

Residual Chi-Square Test		
Chi-Square	DF	Pr > ChiSq
0.6392	2	0.7264

Note: No additional effects met the 0.05 significance level for removal from the model

Summary of Backward Elimination					
Step	Effect Removed	DF	Number In	Wald Chi-Square	Pr > ChiSq
1	Population Estimate_L	1	6	0.0938	0.7594
2	Percent Uninsured	1	5	0.5471	0.4595

Table 4.15: Analysis of maximum Likelihood of Estimates results for Model 3

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-3.3947	3.4837	0.9495	0.3298
Heart Failure Readmission	1	0.3848	0.1023	14.1574	0.0002
PN_6	1	-0.0535	0.0185	8.3754	0.0038
PN_3B	1	-0.0646	0.0272	5.6445	0.0175
Number of Hospitals	1	0.5967	0.1685	12.5426	0.0004
Disadvantaged Population_2	1	1.8700	0.4208	19.7484	<.0001

Table 4.16: Odds ratio Estimates results for Model 3

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
Heart failure Readmission	1.469	1.202	1.795
PN_6	0.948	0.914	0.983
PN_3B	0.937	0.889	0.989
Number of Hospitals	1.816	1.305	2.527
Disadvantaged Population_2	6.488	2.844	14.802

Table 4.17: Association of Predicted Probabilities and Observed Responses results for Model 3

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	86.9	Somers' D	0.741
Percent Discordant	12.8	Gamma	0.743
Percent Tied	0.3	Tau-a	0.188
Pairs	17325	c	0.870

Table 4.18: Goodness of Fit Test results for Model 3

Hosmer and Lemeshow Goodness-of-Fit Test		
Chi-Square	DF	Pr > ChiSq
8.2114	8	0.4131

--END OF MODEL 3--

At 95% confidence level, variables PN_3B, PN_6, Heart Failure Readmission, Disadvantaged Population_2 and Number of Hospitals are significant ($p<0.05$). This combined model from financial importance and operational importance variables will be used for final model formation to predict the closure of rural hospitals.

The good of fit test (Hosmer and Lemeshow test) yields a significant p-value of 0.0879 (>0.05) which implies the model is acceptable and fits the data well.

The concordance percentage value of 87.6% and the Somer's D value of 75.4% are high relative to low discordance (12.1%) which indicates the observed pairs predict a higher probability of an event of closure.

Odds ratio estimates evaluation:

The odds ratio for Heart Failure Readmission is 1.469. An one percent increase in heart failure readmission will increase the risk of closure by 46.9%.

The odds ratio for PN_6 is 0.948. In percentage terms, an one percent increase in PN_6 compliance reduces the odds of closure by 5.2%

The odds ratio for PN_3B is 0.937. In percentage terms, an one percent increase in PN_3B compliance reduces the odds of closure by 6.3%

The odds ratio for Number of Hospitals is 1.816. An increase of one hospital in a county increases the odds of closure by 81.6%

The odds of closure of hospitals in disadvantaged_population_2 locality over in disadvantaged_population_1 locality is 6.488. In percentage terms, odds of closure of hospitals located where disadvantaged population of greater than or equal to 1000 reside is 548.8% higher than hospitals located where disadvantaged population of less than 1000 reside.

Table 4.19: Summary of Significant Predictors for Final Model

Variable	Estimates	Wald Chi-Square
Number of Hospitals	0.5967	12.5426
PN_3B	-0.0646	5.6445
PN_6	-0.0535	8.3754
Heart Failure Readmission	0.3848	14.1574
Disadvantage Population_2	1.87	19.7484

4.1.6.4 Model Formation for Predicting Hospital Closures

Natural log of odds ratio is equivalent to linear function of independent variables.

$$\text{Logit }(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots. + \beta_k x_k$$

Where β_0 = Intercept term

$\beta_1, \beta_2, \ldots, \beta_k$ are estimated parameters.

$x_1, x_2, \ldots, x_k$ are the independent variables

The antilog of the odds ratio will result with the estimated regression equation.

$$\left(\frac{p}{1-p}\right) = e^{\beta 0 + \beta 1 x 1 + \beta 2 x 2 + \cdots \ldots + \beta k x k}$$

Solving for p

$$\Rightarrow \qquad p = \frac{e^{\beta 0 + \beta 1 x 1 + \beta 2 x 2 + \cdots \ldots + \beta k x k}}{1 + e^{\beta 0 + \beta 1 x 1 + \beta 2 x 2 + \cdots \ldots + \beta k x k}}$$

The estimated regression equation is given by

$$\hat{p} = \frac{e^{-3.3947 - 0.0646 PN3B - 0.0535 PN6 + 0.5967 NOH + 1.87 DP2 + 0.38 HFR}}{1 + e^{-3.3947 - 0.0646 PN3B - 0.0535 PN6 + 0.5967 NOH + 1.87 DP2 + 0.38 HFR}}$$

where

NOH- Number of Hospitals

DP2- Disadvantaged Population_2

HFR- Heart Failure Readmission

PN3B- PN_3B

PN6- PN_6

Sample Calculation for Predicted Probability

To validate the model formed above for its predictive capability, a random observation is chosen and the predicted probability is manually calculated and compared with the model system calculated predicted probability. Finally, the probability is will then be compared with the cut-off probability to see where the predicted probability lies, i.e., in the closure group or in the non-closure group and hence the model's predictive ability is determined. Here, observation 157 is chosen and the system generated predicted probability is 0.115.

Let the above probability be compared with the manually calculated predicted probability using the variable parameters and the estimated regression equation as shown below.

PN_3B =92; PN_6 = 85; Number of Hospitals = 1; Disadvantaged Population = 1;

Heart Failure Readmission = 24.4.

$$\hat{p} = \frac{e^{-3.3947-0.0646(92)-0.0535(85)+0.5967(1)+1.87(1)+0.38(24.4)}}{1+e^{-3.3947-0.0646(92)-0.0535(85)+0.5967(1)+1.87(1)+0.38(24.4)}}$$

$$= \frac{e^{-2.1467}}{1+e^{-2.1467}} = \frac{0.11687}{1+0.11687} = 0.10464$$

Hence $\hat{p}$= 0.10464

The predicted probability calculated using the estimated regression equation is 0.10464 with a difference of 0.01 from the system generated probability value of 0.115. This calculated value is lesser than the cut-off probability value of 0.157 (details on calculating the cut-off probability is explained in the model validation part) which means that this observation will be in the non-closure (open) hospital group which is true for the fact that this hospital is originally an open hospital. Hence the model was correct in its prediction.

4.1.7 Model Validation

4.1.7.1 Overview

For model validation purposes, a series of diagnostics tests were performed to primarily evaluate the model's discrimination ability. A model's discriminatory power refers to the capability of the model to correctly discriminate closures and non-closures.

4.1.7.2 Kolmogorov-Smirnov Statistic

The Kolmogorov-Smirnov(K-S) test is one such measure to evaluate the differences in two distribution functions and hence tests the ability of the logistic model to discriminate between closure and non-closure. It is a measure that identifies the maximum separation distance between the cumulative distribution function (CDF) of positive and negative distributions known as K-S Statistic. To calculate the K-S Statistic, 10 deciles are created, then the percentage of closure and non-closure are calculated for each corresponding decile. Finally, the cumulative percentages of closures and non-closures are calculated. The difference between the cumulative percentage of closure and non-closure for each decile is calculated. The K-S Statistic is identified by the largest value difference between the cumulative percentage of closure and non-closure.

For the training data, the K-S Statistic resulted with 60.9%, which is acceptable per the K-S Statistic guidelines such that the K-S Statistic value should be between 40 and 70. Similarly, the Kolmogorov-

Smirnov statistic was calculated for the testing data and resulted with 54.1%, which is acceptable again per guidelines.

Table 4.20: Kolmogorov- Smirnov Statistics Table for Training Data

Decile	Closure	Non_Closure	% of all Closure	% of all Non-Closure	Cum. % Closure	Cum. % Non-Closure	K-S Statistic
~10%	26	11	47.3%	3.5%	47.3%	3.5%	43.8%
~20%	12	25	21.8%	7.9%	69.1%	11.4%	57.7%
~30%	7	30	12.7%	9.5%	81.8%	21.0%	60.9%
~40%	2	35	3.6%	11.1%	85.5%	32.1%	53.4%
~50%	1	36	1.8%	11.4%	87.3%	43.5%	43.8%
~60%	4	33	7.3%	10.5%	94.5%	54.0%	40.6%
~70%	1	36	1.8%	11.4%	96.4%	65.4%	31.0%
~80%	2	35	3.6%	11.1%	100.0%	76.5%	23.5%
~90%	0	37	0.0%	11.7%	100.0%	88.3%	11.7%
~100%	0	37	0.0%	11.7%	100.0%	100.0%	0.0%
Totals	55	315				KS	60.9%

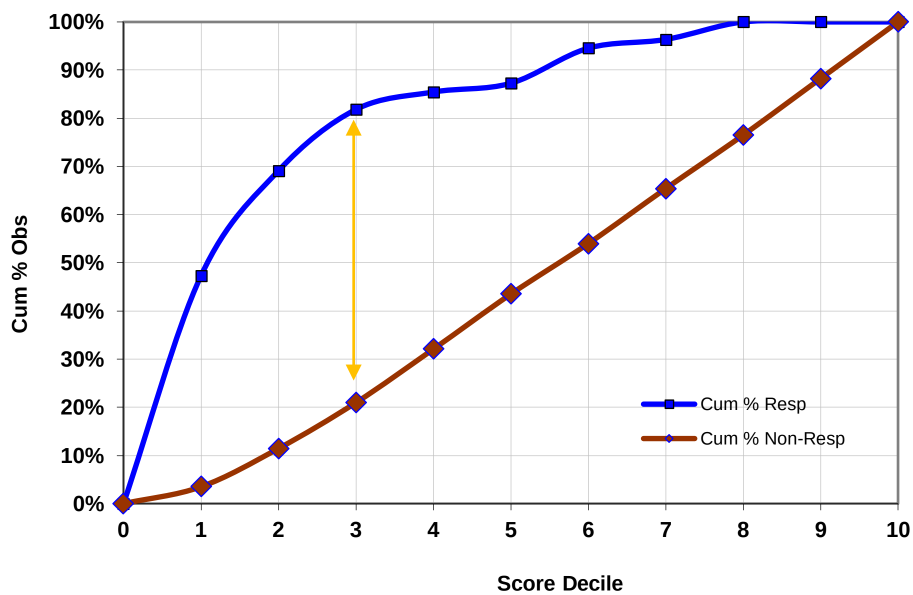


Figure 4.16: Kolmogorov-Smirnov Graph for Model Formation Data

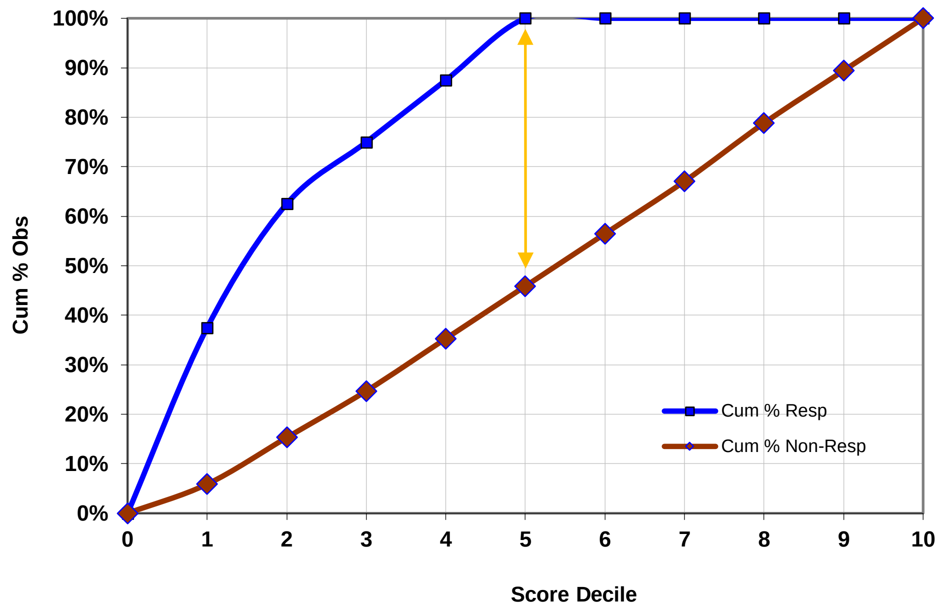


Figure 4.17: Kolmogorov-Smirnov Graph for Model Validation Data

4.1.7.3 Receiver Operator Curve (ROC)

Another way to determine the discriminatory ability of the model is by using Sensitivity and Specificity of the model. Sensitivity refers to the probability of predicting closure when closure is the outcome and Specificity is the probability of predicting non-closure when non-closure is the outcome.

Hosmer and Lemeshow suggested a method to create classification table by selecting the cutoff point at which the Sensitivity and Specificity are equal (Mernard). Similarly, the cutoff point is chosen, when the Sensitivity and Specificity are equal. The plot below shows the Specificity and Sensitivity curves when they are plotted from 1(100%) to 0 (0%) and 0 (0%) to 1(100%) respectively. The point where the two curves meet is where the Sensitivity and Specificity are equal, is chosen as the cut-off point. A classification table is created based on this cut-off value.

From the analysis table, when p=0.157, the sensitivity and specificity are about equal to 0.81.

Table 4.21: Sensitivity and Specificity Cut off point Summary Table

Probability	No. of Correctly Predicted Events	No. of Correctly Predicted Nonevents	No. of Nonevents Predicted as Events	No. of Events Predicted as Nonevents	Sensitivity	Specificity	1 - Specificity
0.157	45	254	61	10	0.81	0.806	0.193651

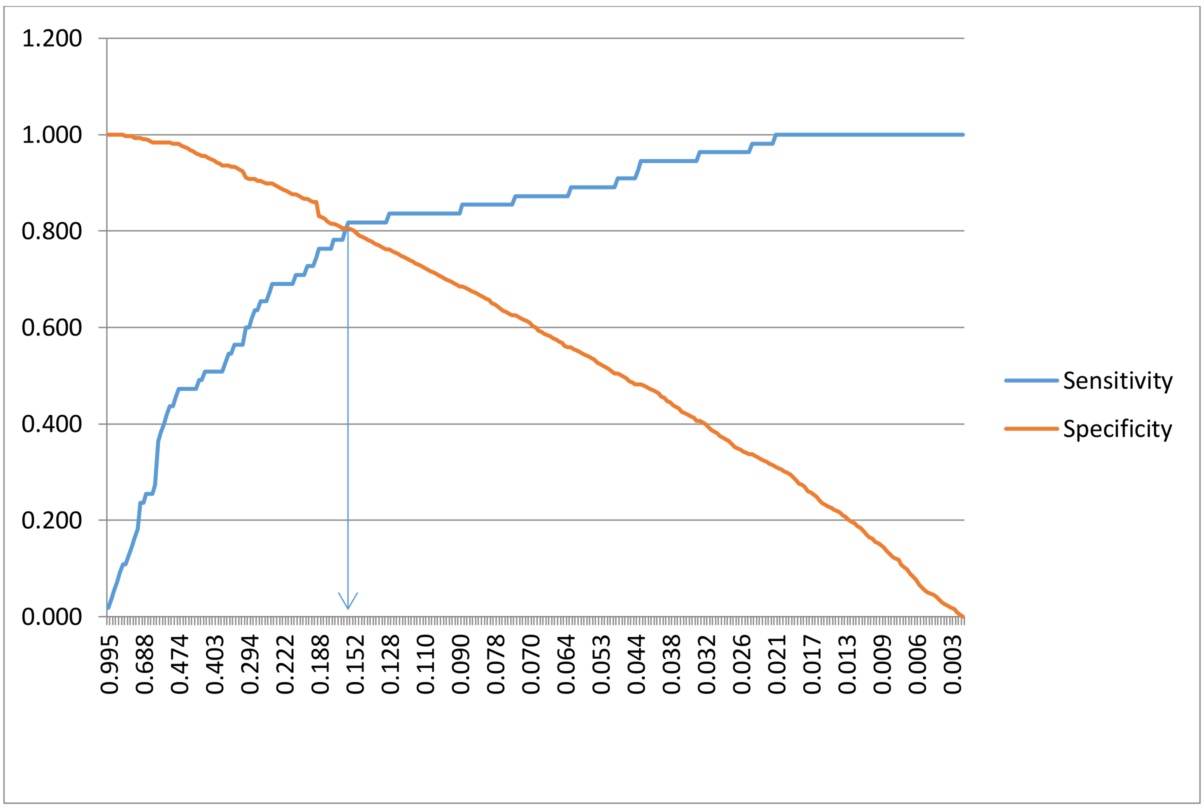


Figure 4.18: Sensitivity and Specificity cut off point graph

4.1.7.3.a Classification and ROC Testing for Model Formation Data

A classification table created using the training data is show below. The purpose is to determine how well the model could correctly classify closures and non-closures.

Table 4.22: Classification Table for Model Formation Data

Training Data-Classification Table			
	Closed-1, Open-0		Total
Closed-1, Open-0	0	1	
0	254	10	271
1	61	45	99
Total	315	55	370

The classification table results show the model correctly classified 45 hospitals as closed and incorrectly classified 10 as closed, i.e., the model correctly predicted closure about 81%. Classification table also shows that the model correctly predicted non-closure about 81% by correctly classifying 254 hospitals as non-closure and incorrectly classifying 61 hospitals as non-closure. For both cases, higher the value, better the model's ability for classification.

Sensitivity and Specificity may also be used as a basis for calculating a measure of explained variation (Mernard). Here, the Sensitivity is plotted on the y-axis and 1-Specificity is plotted on the x-axis generating a curve known Receiver Operating Characteristic curve (ROC Curve). The accuracy of the model is the ability of itself to correctly discriminate closures and non-closures. One measure of accuracy is the area under the curve (AUC). In general, higher the area under the ROC curve, better is the model to correctly classify events (Closure and Non-closure).

By Hosmer and Lemeshow's general rules for interpreting AUC values, the following guidelines are given.

AUC = 0.5 (No Discrimination)

0.7 ≤ AUC < 0.8 (Acceptable Discrimination)

0.8 ≤ AUC < 0.9 (Excellent Discrimination)

AUC ≥ 0.9 (Outstanding Discrimination)

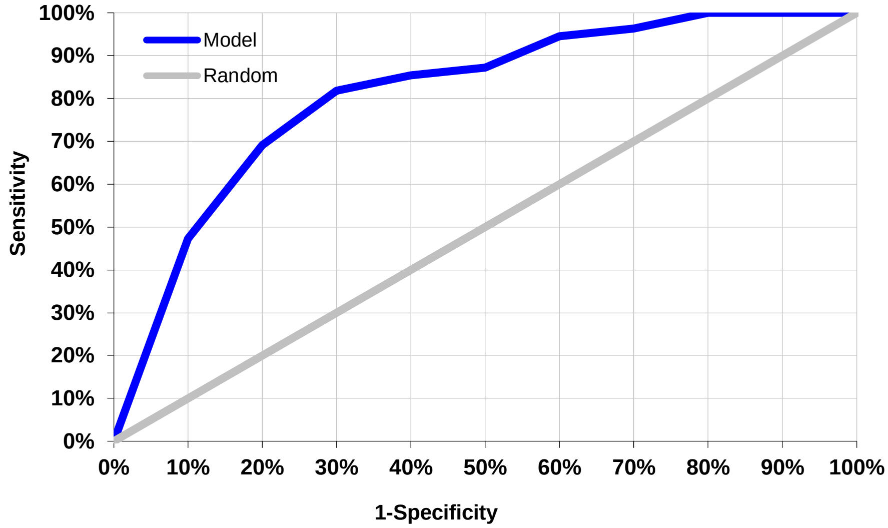


Figure 4.19: Receiver Operating Curve for Model Formation Data

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	86.9	Somers' D	0.741
Percent Discordant	12.8	Gamma	0.743
Percent Tied	0.3	Tau-a	0.188
Pairs	17325	c	0.870

The AUC is given by the C-statistic from the table which is .87 or 87%. In terms of its discriminatory power in accordance with the above guidelines, the model's discriminatory power is excellent.

4.1.7.3.b Classification and ROC testing for Validation data

A classification table for the validation data was created using the p-value equal to 0.157 and the results are shown in the table below.

Table 4.23: Classification Table for Model Validation Data

Validation Data-Classification Table			
	Closed-1, Open-0		Total
Closed-1, Open-0	0	1	
0	64	3	72
1	18	5	21
Total	85	8	93

From the classification table for the validation data, the model correctly classified 5 hospitals as closed and incorrectly classified 3 as closed, i.e., the sensitivity is 62.5%. Also, the model correctly classified 64 hospitals as non-closure and incorrectly classified 18 as non-closure and hence the specificity of the model is 75%. The overall accuracy of the model is 74%. An ROC curve plotted for the validation model using Sensitivity and 1-Specificity is shown below.

The area under the ROC curve is 85%, which implies the model's discriminatory ability is excellent. The AUC for model formation and validation are 87% and 85% respectively, which is approximately in the same range and have suggested that both models are performing well in terms of classifying closure events and non-closure events.

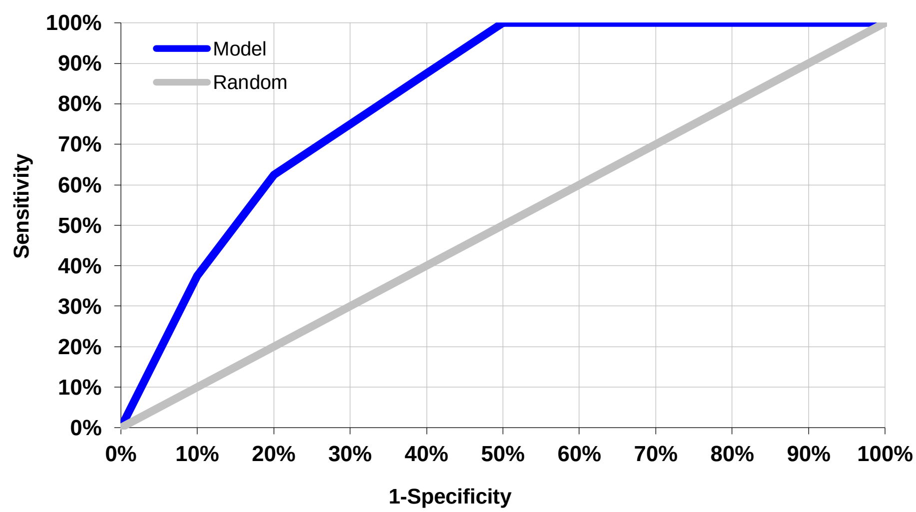


Figure 4.20: Receiver Operating Curve for Model Validation Data

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	82.1	Somers' D	0.642
Percent Discordant	17.9	Gamma	0.645
Percent Tied	0	Tau-a	.158
Pairs	680	c	0.85

4.2 Deployment and Evaluation of Lean Six Sigma Project Initiatives

4.2.1 Scenario 1 Results

Different scenarios were run by adjusting the yellow belt, green belt and black belt project types. Like discussed in the methodology section, the idea is to limit the black belt projects due to limited resources available on the same. Also, by having a minimum number of yellow belt and green belt projects will ensure the effectiveness of Six Sigma will be realized soon to instill belief in the management and stakeholders. The optimal results were obtained when the model parameters for scenario 1 were set such that there are at least 3 yellow belt projects and 2 green belt projects are implemented during the pilot phase.

Table 4.24: Model Parameters table

Scenario: 1		Scenario: 2	
Y_{ij}	3	A	3
G_{ij}	2		
B	$1,000,000	B	$1,000,000

In effect, the model for scenario 1 resulted with a cost savings of $2,838,871 with an investment cost of $999,576. In total, eight projects were chosen, in which 4 projects were chosen from hospital 2 and 4 projects were chosen from hospital 3. Among them, 2 yellow belt & 2 black belt projects were chosen from hospital 2 and 1 yellow belt, 2 green belt & 1 black belt projects were chosen from hospital 3. The table below depicts the results in detail.

Table 4.25: Scenario 1- Model Results Summary

Total Maximized Cost Savings	$2,838,871
Total Investment Cost	$999,576
Total Number of projects selected	8
Number of Yellow Belt projects selected	3
Number of Green Belt projects selected	2
Number of Black Belt projects selected	3

4.2.2. Scenario 2 Results

Scenario 2 was run by limiting the black belt projects as the 3 core measure projects identified in hospital 3 have 2 black belt projects among them. The optimal results were obtained when the black belt projects were limited to 3. The model for scenario 2 resulted with a cost savings of $2,624,783. In total, seven projects were selected from hospitals 2 and 3, among which 2 yellow belt & 1 black belt projects were selected from hospital 2 and 2 green belt & 2 black belt projects were chosen from hospital 3. The three core measure projects from hospital 3 includes 2 black belt and 1 green belt project. The total investment for the overall deployment is $998,465. The table below depicts the results in detail.

Table 4.26: Scenario 2- Model Results Summary

Total Maximized Cost Savings	$2,624,783
Total Investment cost	$998,465
Total Number of projects selected	7
Number of Yellow Belt projects selected	2
Number of Green Belt projects selected	2
Number of Black Belt projects selected	3

4.2.3 Net Present Value Evaluation of Lean Six Sigma Projects Deployment Decision

A Net Present Value(NPV) evaluation of the project deployment will enable to determine if it would be economically feasible for hospital management. It is assumed that the projects will generate equal annual returns of the savings amount for the cash flow during a period of 3 years and for an interest rate of 12%. NPV is calculated for both scenarios to determine if the deployment is worthwhile the investment for the management.

Scenario 1:

NPV = -\$1,000,000 + \$2,838,871 (P/A 12%, 3)

= \$95,112

Here, the NPV is >0, hence deploying Lean Six Sigma projects is acceptable.

Scenario 2:

NPV = -\$1,000,000 + \$2,624,783 (P/A 12%, 3)

= \$93,740

Here, in scenario 2, the NPV is >0 as well. Hence deploying Lean Six Sigma projects is acceptable

Conclusion:

Although the cost savings realized from implementing Lean Six Sigma projects will not eliminate the closure risks in one sweep, the initial savings from the pilot phase of implementation will alleviate the risks to some degree. Also, by focusing on improving core measure processes, hospitals can avoid unnecessary costs, as well as avoid penalties and can leverage the programs such as HVBP to receive incentives for good quality of care. As more projects are implemented in the later phases, by strategically implementing projects based on the needs, the hospitals can achieve cost savings, generate additional revenues and improve the profit margin, thus eliminating the closure issues.

Chapter: 5

Contribution to the Body of Knowledge

IE 5300-RFID in Logistics

The lab experiments performed in this course helped in experimentally studying and conducting research.

IE 5312- Planning and Control of Enterprise Systems

Understanding Hospital Enterprise as a system with the complex nature of processes & activities involved and identifying key stakeholders involved at different levels of the processes.

IE 5304-Engineering Economy

Understanding the economics is vital for this project. Costs reduction, improving revenue and profit are the key for the hospitals to prevent closures in the future.

IE 5303- Quality Systems

Understanding the concepts of quality, the tools and the methodology used for quality improvement.

IE 5342- Metrics and Measurements

Standardizing care and other related processes will help hospitals in achieving efficiency and generate additional revenue yielding opportunities.

Chapter 6

Conclusions and Discussions

6.1 Conclusions

The motivation behind this project is the wave of rural closures happening since 2010 on an increasing trend till date around the country. The project started with background study of closures occurring throughout the country but majority of the closures happening in the southern region of the country (Texas being the state with maximum number of closures).

The background research gave an idea that the variables identified can be classified as Operational Importance and Financial Importance variables to analyze separately. The statistical analysis that was performed on the potential variables resulted with 5 significant predictors in total, among which 3 variables are from operational importance model and 2 are from financial importance model to be significant in predicting hospital closures. The model validation analysis proved the model to be accurately predicting closures with a discriminatory capability of 87% and 85% using model formation and model validation data's respectively.

The analyses from research objective 2 shows that there are some lapses in care exists within the hospital which may affect the hospital closures. For instance, Heart Failure Readmission is proved to predict closure, meaning closed hospitals haven't adequately taken measures to prevent patients coming back within 30 days for the same diagnosis, which results in unnecessary costs as well as more likelihood of receiving penalties.

The results from the Lean Six Sigma deployment shows hospitals can bring in the present situation in control when they start making changes within their system. The savings realized from the quality improvement efforts through Lean Six Sigma during the pilot phase should bring in confidence and improved morale among the top management and employees. Although the initial cost savings will not completely change the financial status and eliminate risks for the hospitals, in the long run, identifying and implementing more projects based on the needs of the patients, needs of business goals and needs of the process will bring in transformation of the enterprise to achieve operational excellence. The transformation may attract more patients and create a win-win situation for the hospitals to save costs by improving quality as well as gain revenue by improving utilization rate and patient volume which has been long standing issue for rural hospitals. The improvement efforts should also be able to provide immunity to hospitals to some extent against poor socioeconomic conditions in hospital's vicinity as well as any policy changes in the future that may hamper the existence of these hospitals. The inclusion of hospitals in disadvantaged locations for strategic improvements will make sure that the patients that depend on those hospitals will get adequate and timely care.

6.2 Limitations

Many literatures lacked cost savings data associated with Six Sigma projects with many did not quantified cost savings as limited projects could be used for the study.

Although data couldn't be collected from open and closed hospitals for confidentiality reasons, the publicly made available data, especially the hospital compare data on hospitals process performance was attainable.

6.3 Future work

This study has unveiled several future opportunities for research in this area. Projects can be planned to implemented on a multi-phase basis if more feasible projects could be identified. Also, hospitals can target to have a good project mix by targeting efficiency as well as projects that focus on patient satisfaction, which will help rural hospitals to get the trust from patients and may translate in to hard and soft savings.

This research has opened the avenue for improvements in hospitals located in disadvantaged locations. Hospitals in disadvantaged locations can develop strategies to attain process improvements throughout the hospital to attract more patients and thereby improving revenue and profit.

APPENDIX

Appendix A: Predicted Probabilities

S. NO	Probability		S.NO	Probability		S.NO	Probability		S.NO	Probability
1	0.045474		36	0.006633		71	0.403086		106	0.151757
2	0.031347		37	0.005563		72	0.107878		107	0.599678
3	0.170528		38	0.002678		73	0.264548		108	0.040923
4	0.065235		39	0.141782		74	0.063556		109	0.039872
5	0.013524		40	0.110254		75	0.404734		110	0.459233
6	0.062943		41	0.187571		76	0.019558		111	0.075023
7	0.209116		42	0.109493		77	0.02248		112	0.114413
8	0.026538		43	0.095033		78	0.617078		113	0.460231
9	0.006555		44	0.006394		79	0.873406		114	0.915913
10	0.187571		45	0.039665		80	0.73123		115	0.003605
11	0.053484		46	0.077891		81	0.437394		116	0.007192
12	0.013353		47	0.010104		82	0.187571		117	0.017225
13	0.015263		48	0.538668		83	0.146304		118	0.138459
14	0.008157		49	0.003166		84	0.207953		119	0.040736
15	0.00374		50	0.004804		85	0.200823		120	0.295436
16	0.187571		51	0.215333		86	0.050887		121	0.009974
17	0.090487		52	0.038511		87	0.281351		122	0.455628
18	0.599678		53	0.070087		88	0.065686		123	0.086065
19	0.146272		54	0.003905		89	0.295436		124	0.006061
20	0.044895		55	0.070418		90	0.040612		125	0.006933
21	0.067735		56	0.007084		91	0.109385		126	0.011096
22	0.240097		57	0.044291		92	0.056538		127	0.005648
23	0.418124		58	0.002741		93	0.09364		128	0.032456
24	0.542687		59	0.157611		94	0.087648		129	0.008152
25	0.005352		60	0.105138		95	0.01073		130	0.089826
26	0.868915		61	0.027272		96	0.033276		131	0.118151
27	0.046131		62	0.076675		97	0.140882		132	0.400522
28	0.006392		63	0.831685		98	0.033163		133	0.619628
29	0.00495		64	0.024658		99	0.091988		134	0.024106
30	0.064161		65	0.007018		100	0.053478		135	0.016535
31	0.106308		66	0.058775		101	0.011148		136	0.066869
32	0.754781		67	0.021326		102	0.029959		137	0.432323
33	0.067735		68	0.008971		103	0.004053		138	0.00445
34	0.373152		69	0.037357		104	0.012534		139	0.599678
35	0.010584		70	0.014094		105	0.092547		140	0.295436

S.NO	Probability		S.NO	Probability		S.NO	Probability		S.NO	Probability
141	0.019957		176	0.373424		211	0.038441		246	0.069658
142	0.388566		177	0.015669		212	0.015266		247	0.057748
143	0.127745		178	0.023819		213	0.050135		248	0.599678
144	0.023924		179	0.183736		214	0.030578		249	0.442808
145	0.140447		180	0.010905		215	0.035103		250	0.353565
146	0.026262		181	0.885007		216	0.432323		251	0.008918
147	0.546696		182	0.505351		217	0.066658		252	0.022361
148	0.018107		183	0.128412		218	0.018641		253	0.044845
149	0.069758		184	0.038378		219	0.06789		254	0.042828
150	0.189625		185	0.111722		220	0.036346		255	0.047694
151	0.276304		186	0.295436		221	0.087174		256	0.865521
152	0.016895		187	0.015745		222	0.014939		257	0.124903
153	0.156914		188	0.116748		223	0.074817		258	0.015405
154	0.036515		189	0.028324		224	0.599678		259	0.012904
155	0.054881		190	0.139169		225	0.032297		260	0.872538
156	0.115587		191	0.187571		226	0.130977		261	0.021879
157	0.02366		192	0.995437		227	0.088619		262	0.083953
158	0.170474		193	0.026005		228	0.008738		263	0.189134
159	0.069582		194	0.003941		229	0.008748		264	0.045762
160	0.007805		195	0.05008		230	0.047194		265	0.015457
161	0.018165		196	0.010908		231	0.063591		266	0.003345
162	0.293537		197	0.02044		232	0.187571		267	0.005265
163	0.295436		198	0.00945		233	0.011426		268	0.009864
164	0.040131		199	0.220842		234	0.031747		269	0.73123
165	0.214058		200	0.640265		235	0.097598		270	0.033018
166	0.164123		201	0.0357		236	0.382828		271	0.25088
167	0.515363		202	0.208354		237	0.005449		272	0.030013
168	0.078067		203	0.42678		238	0.041278		273	0.029784
169	0.041585		204	0.007747		239	0.224837		274	0.017506
170	0.020874		205	0.070536		240	0.016673		275	0.03726
171	0.550378		206	0.027346		241	0.007118		276	0.035761
172	0.168576		207	0.687669		242	0.007689		277	0.010605
173	0.065434		208	0.167228		243	0.063699		278	0.002619
174	0.078044		209	0.866069		244	0.003038		279	0.266747
175	0.333246		210	0.056929		245	0.007447		280	0.13281

S.NO	Probability		S.NO	Probability		S.NO	Probability
281	0.124447		311	0.970365		341	0.039823
282	0.013004		312	0.091642		342	0.087899
283	0.202824		313	0.011198		343	0.12259
284	0.066457		314	0.163218		344	0.075304
285	0.275293		315	0.030326		345	0.020097
286	0.032505		316	0.032105		346	0.076675
287	0.0708		317	0.323028		347	0.073083
288	0.187571		318	0.031406		348	0.002005
289	0.05466		319	0.003799		349	0.222387
290	0.030886		320	0.295436		350	0.678622
291	0.012591		321	0.021675		351	0.006596
292	0.088296		322	0.021241		352	0.071015
293	0.062684		323	0.012117		353	0.005662
294	0.425411		324	0.028998		354	0.23635
295	0.171554		325	0.19683		355	0.018708
296	0.010779		326	0.73123		356	0.187571
297	0.007214		327	0.831685		357	0.01509
298	0.050552		328	0.311437		358	0.473672
299	0.016827		329	0.471444		359	0.153672
300	0.057341		330	0.051478		360	0.231533
301	0.00998		331	0.006134		361	0.272247
302	0.138862		332	0.053039		362	0.021386
303	0.002833		333	0.012804		363	0.060124
304	0.187571		334	0.077687		364	0.043681
305	0.187571		335	0.030863		365	0.082658
306	0.026365		336	0.144452		366	0.120885
307	0.081123		337	0.043887		367	0.016911
308	0.115362		338	0.019527		368	0.322757
309	0.025624		339	0.005244		369	0.157329
310	0.026508		340	0.130176		370	0.013772

Appendix B

Area Under the ROC Curve calculation

Table 1: Model Formation Data

Approx. score %-ile	Closures	Non Closures	Response Rate	% of all Closures	% of all Non-Closures	Cum. % Closures	Cum. % Non-Closures	Gini Calc
~10%	26	11	70.3%	47.3%	3.5%	47.3%	3.5%	0.0083
~20%	12	25	32.4%	21.8%	7.9%	69.1%	11.4%	0.0462
~30%	7	30	18.9%	12.7%	9.5%	81.8%	21.0%	0.0719
~40%	2	35	5.4%	3.6%	11.1%	85.5%	32.1%	0.0929
~50%	1	36	2.7%	1.8%	11.4%	87.3%	43.5%	0.0987
~60%	4	33	10.8%	7.3%	10.5%	94.5%	54.0%	0.0952
~70%	1	36	2.7%	1.8%	11.4%	96.4%	65.4%	0.1091
~80%	2	35	5.4%	3.6%	11.1%	100.0%	76.5%	0.1091
~90%	0	37	0.0%	0.0%	11.7%	100.0%	88.3%	0.1175
~100%	0	37	0.0%	0.0%	11.7%	100.0%	100.0%	0.1175
Totals	55	315	14.86%				AUC	87%

Table 2: Model Validation Data

Approx. score Percentile	Closures	Non-Closures	Response Rate	% of all Closures	% of all Non-Closures	Cum. % Closures	Cum. % Non-Closures	Gini Calc
~10%	3	5	37.5%	37.5%	5.9%	37.5%	5.9%	0.0110
~20%	2	8	20.0%	25.0%	9.4%	62.5%	15.3%	0.0471
~30%	1	8	11.1%	12.5%	9.4%	75.0%	24.7%	0.0647
~40%	1	9	10.0%	12.5%	10.6%	87.5%	35.3%	0.0860
~50%	1	9	10.0%	12.5%	10.6%	100.0%	45.9%	0.0993
~60%	0	9	0.0%	0.0%	10.6%	100.0%	56.5%	0.1059
~70%	0	9	0.0%	0.0%	10.6%	100.0%	67.1%	0.1059
~80%	0	10	0.0%	0.0%	11.8%	100.0%	78.8%	0.1176
~90%	0	9	0.0%	0.0%	10.6%	100.0%	89.4%	0.1059
~100%	0	9	0.0%	0.0%	10.6%	100.0%	100.0%	0.1059
Totals	8	85	8.6%				AUC	85%

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