A MODEL CHARACTERIZATION OF THE TEXAS HEALTHCARE FACILITIES IMPACTED BY THE 2013 MEDICARE PENALTIES: A FRAMEWORK FOR SELF EVALUATION AND SYSTEMIC PREEMPTIVE ACTION TO REDUCE HIGH HOSPITAL READMISSION RATES

by

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Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT ARLINGTON

May 2013

ACKNOWLEDGEMENTS

First, I would like to thank the chair of my dissertation committee, my advisor and mentor, Dr. Erick C. Jones. I thank you for the challenges, guidance and motivation to “get the job done”. Thank you for being patient with me and for continuing to believe in me and my abilities.

I would also like to thank the members of my dissertation committee – Dr. D. Liles, Dr. R. Mintz-Binder, Dr. J. Rogers and Dr. L. Zeng. Thank you for being a part of this academic journey. Your contributions, both large and small alike, were truly appreciated.

To my wonderful mother: I am extremely humbled when I recall the tremendous sacrifices you made for your six children. You became a widow at such a young age, but you set the perfect example of achieving goals as you raised your children by yourself, attended college and worked three jobs. I knew I could not dare complain about how difficult this journey was. You taught us to trust God for all things; for He alone was your secret weapon for rising above the difficult hand you were dealt. Your life was the ideal pattern I wanted to mimic – no complaints, sheer determination. You have made me who I am today, and I thank you and love you.

To my dad: after so many years you are still missed. The song “Gone Too Soon” comes to mind every time I think about you. Your passion and love for life is still very real to me. Your memories continue to motivate me to face difficulties head on. You are missed and I love you.

To my siblings, their spouses and children: thanks for the words of encouragement and continued support. The occasional weekend family gatherings, where we simply enjoyed each other’s company and ended the night with dance, were critical for preparing my mind for more studies.

To my children, LeNaiya and LeMaur: you guys are my world! Although my days were hectic and sometimes impossible, your smiles and hugs were a constant reminder

of the underlying reasons I decided to engage in an academic challenge such as this. One of my greatest desires is to inspire both of you to always strive for excellence, and with unwavering perseverance, you will succeed. Love you guys!

To my husband and best friend, Conroy: I present you with a big Thank You! Thank you for the support and for allowing me to pursue my personal goals. You have sacrificed a great deal, and I appreciate all you have done.

Finally, to my ultimate cheerleader, encourager, provider and inspiration, my God: without you I am nothing. Thank you for guiding my thoughts and directing my path. You are so real to me, and You are simply awesome. Thank you.

I can do all things through Christ which strengthens me. Philippians 4:13

April 29, 2013

ABSTRACT

THE CHARACTERIZATION OF THE TEXAS HEALTHCARE FACILITIES
IMPACTED BY THE 2013 MEDICARE PENALTIES: A FRAMEWORK FOR SELF
EVALUATION AND SYSTEMIC PREEMPTIVE ACTION TO
REDUCE HIGH HOSPITAL READMISSION RATES

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The Patient Protect and Affordable Care Act of 2010 became a law on March 23, 2010. This healthcare act, according to the authors, is designed to improve health services by targeting various facets of the industry: hospitals, private physicians, insurance companies and the drug industry – to name a few. It impacts many people, both directly and indirectly. The effects of this new law will most likely not immediately be recognized, although is it possible for "pockets: of success stories.

The administration of Medicare is an area of interest primarily because of the finances involved. Today, there are many waste streams tied to Medicare and it has become an annual billion dollar problem. Medicare was instituted to take care of the elderly of this nation and a few others with special illnesses; however, the systems that are currently in place to drive this program are performing as they should.

About $18 billion dollars is poured in the Medicare system every year to pay for services related to hospital readmissions. This has really become an issue, and hospitals and the

federal government alike, are trying to understand what's happening and why it's happening, the end goal of fixing the problems and reducing readmission rates.

A part of the healthcare Act is focused on reducing costs related to readmissions. A penalty program was established and implemented beginning October 2012, and each October moving forward, up to three rounds of penalties (2015), hospitals with high hospital readmission rates will receive these penalties. The 2012 -2013 fiscal year had a maximum penalty of 1%, but that amount will increase up to 3% in the 2015-2016 fiscal year.

The state of Texas was the second highest state, in terms of number of hospitals receiving penalties – California was top on the list. There were 315 hospitals slated for Medicare review, but some hospitals were fortunate enough to be eliminated from the penalty list.

The goal of this study was to determine if a model could be constructed to predict if a Texas hospital would be penalized. The access to actual data is very limited in the healthcare industry, so the data collection plan consisted of obtaining data from reputable sources such as the Center for Medicare and Medicaid Services (CMS).

The data collected was analyzed using a binary logistic regression, with following responses (Penalized, Not Penalized). The predictor variables were taken from three key process steps: (1) Input to Hospital, (2) Operations within hospital, and (3) Output (discharge processes). From a count of 42 initial predictors, a model with a discrimination value of AUC = 0.75 and 6 predictors was constructed. The model is statistically sound and has merit, and hospitals, in the state of Texas, can utilize this model, recognizing its limitations, to predict whether or not they will be penalized.

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**** A ****

AHRQ – Agency for Healthcare Research and Quality

AUC – Area Under Curve

**** C ****

CFR – Code of Federal Regulations

CMS – Centers for Medicare & Medicaid Services

**** D ****

DRG – Diagnosis-related Group

**** H ****

HCAHPS – Hospital Consumer Assessment of Healthcare Providers and Systems

**** I ****

IPPS – Inpatient Prospective Payment Service

**** R ****

ROC – Receiver Operating Characteristic

**** S ****

SNF – Skilled Nursing Facility

CHAPTER 1

INTRODUCTION

1.1 Overview

1.1.1. Patient Protect and Affordable Care Act of 2010

The Affordable Care Act was passed by Congress and then signed into law by President Barack Obama on March 23, 2010. In the words of the federal government, the "Affordable Care Act puts in place strong consumer protections, provides new coverage options and gives you the tools you need to make informed choices about your health" (Health & Human Services).

The Obama Campaign of 2008 focused on the promise of bringing change from many fronts, in fact, the slogan for his first campaign run was "Change We Can Believe In". His first term certainly did turn out to be a change-oriented one, and his administration was able to successfully pass legislation regarding many things such as: Wall Street reform, affordability of college education, and the most historic and controversial one of all, healthcare reform. (Organizing for Action)

America is divided in its opinion of the healthcare reform that is now law - some accept it in its entirety, some are not opposed to portions of it, and some do not have any regards for any of it. The Obama administration highlights three key aspects of the healthcare law, which is commonly referred to "Obamacare":

- Eradicates the abuse of insurance companies: "The Affordable Care Act is holding insurance companies accountable, putting an end to the worst abuses, such as capping or dropping your coverage when you get sick". (Organizing for Action)

- Strengthens Medicare: “The Affordable Care Act is helping people with Medicare save on the care they need to stay healthy—from free preventive services to lower costs on prescription drugs and monthly premiums”. (Organizing for Action)
- Women have total control of their health: “President Obama is putting an end to the health insurance company practice of charging women more than men for the same coverage”. (Organizing for Action)

These three areas were deemed to be problematic in the past, and the written legislation promises change. It is not realistic for the administration, or the citizens of this country, to believe that results will be realized overnight, so the full impact of these legislations will not be really known for a very long time. However, there will be “pockets” of results that may be favorable or not favorable, but the overriding and underlying effects will require time for maturity.

1.1.2. The Medicare Movement

The federal insurance program that was instituted in 1965 is called Medicare, and it was designed to assist people who are age 65 or older, certain younger people with disabilities, and people with End-Stage Kidney Failure.

Although the entire healthcare system is under scrutiny, Medicare is currently receiving a great deal of attention. It was initially intended to be a service that would benefit patients and hospitals alike, it was supposed to be a program that would bring national pride, knowing that the most vulnerable citizens would have some leverage when it came to healthcare. As years passed by, it actually grew into a financial waste stream.

As was previously mentioned, the Patient Protect and Affordable Care Act of 2010 was instituted to address the growing concerns and issues associated with the health system in America, and these issues stem from many fronts, including the quality of services being rendered by healthcare providers. The sub-standard level of service at some hospitals leads to extremely high costs for insurance providers, both private and federally funded alike.

It is a fact that there are scores of hospitals across this country operating in a high efficient, top quality manner. These facilities are dedicated to providing the best services possible and are making solid investments to truly respond to the needs of their customer base. However, there are hundreds of other hospitals that are not as dedicated, and they become catalysts for creating waste streams, inefficiencies and poor customer service. In all fairness, it is absolutely worth mentioning that the patients also have a key role to play in the high expenditures associated with Medicare. Very often patients fail to follow guidelines for good health and recovery, and they end up tapping into this insurance program, and the overall system, more often than is truly necessary. At some point, under some administration, the Medicare issues would have had to be addressed, and the Obama administration has initiated the process.

1.1.3. Healthcare Reform and Medicare

Medicare policies and procedures were examined, and changes were made. Some of these changes are reflective of the fact that the economy is in poor condition, families are financially challenged and people are living longer. The Affordable Care Act claims to strengthen Medicare. No cost sharing preventive services are offered to eligible seniors, and drugs are provided at discounts when there is a coverage gap.

Four key Medicare elements, some of which were previously mentioned, that were targeted for change, are highlighted below. (Health & Human Services)

- Preventive Services – Medicare participants are eligible for several no cost preventive services.
- Drug Discounts – Eligible seniors in the coverage gap automatically receive a discount on prescription drugs.

- Drug Rebates – Eligible seniors may qualify for a $250 rebate.
- Strengthening Medicare – “The health care law cracks down on waste, fraud, and abuse while providing new protections for seniors”.

There are ten titles to the Affordable Care Act (See Appendix A). The third one is entitled, “Improving the Quality and Efficiency of Healthcare”, and this study is a derivative of this particular title. The summary of this component of the law, as directly stated by the federal government, reads: (Health & Human Services)

> *“The Act will protect and preserve Medicare as a commitment to America’s seniors. It will save thousands of dollars in drug costs for Medicare beneficiaries by closing the coverage gap called the “donut hole.” Doctors, nurses and hospitals will be incentivized to improve care and reduce unnecessary errors that harm patients. And beneficiaries in rural America will benefit as the Act enhances access to health care services in underserved areas”.*

> *“The Act takes important steps to make sure that we can keep the commitment of Medicare for the next generation of seniors by ending massive overpayments to insurance companies that cost American taxpayers tens of billions of dollars per year. As the numbers of Americans without insurance falls, the Act saves taxpayer dollars by keeping people healthier before they join the program and reducing Medicare’s need to pay hospitals to care for the uninsured. And to make sure that the quality of care for seniors drives all of our decisions, a group of doctors and health care experts, not Members of Congress, will be tasked with coming up with their best ideas to improve quality and reduce costs for Medicare beneficiaries”*

It is clear from the summary that the Act was fundamentally installed to maintain the commitment that was made a long time ago to the seniors of this country. Although not everyone agrees with the methods of change, it is a well-accepted fact that something has to be done to make improvements.

1.1.4. The Hospital Readmissions Issue

"Section 3025 of the Affordable Care Act added section 1886(q) to the Social Security Act establishing the Hospital Readmissions Reduction Program, which requires CMS (Centers for Medicare & Medicaid Services) to reduce payments to IPPS (Inpatient Prospective Payment Service) hospitals with excess readmissions, effective for discharges beginning on October 1, 2012. The regulations that implement this provision are in subpart I of 42 CFR part 412 (§412.150 through §412.154)". (Centers for Medicare & Medicaid Services)

Medicare has become a very expensive venture for the federal government over its lifetime, and in our current society, where the economy is severely "wounded" and financial debt is off the charts and at historical levels, it becomes a matter of survival to strive to cut costs and halt the financial waste streams. The federal government has taken action to cut cost and improve healthcare quality by imposing penalties on hospitals with excessively high readmission rates.

Each hospital, based on many factors, has a statistically developed expected readmission projected value. The difference between actual readmissions and expected readmissions (*Excess = Actual – Expected*) is calculated for each hospital at the end of the fiscal reporting year. If the hospital's actual readmission number for a given time period is smaller than the expected value, the calculated number will be negative, and the actual excessive value that is reported out is zero. A hospital is considered to have a high readmission rate if the difference between the two numbers is a positive value. If the actual readmission value, for a given time period, exceeds the projected amount, then the excess becomes a multiplier in the formula that was developed to calculate Medicare readmission penalties.

Due to the many health conditions patients have, these penalties will only be imposed for readmissions associated with heart attack, heart failure and pneumonia. (Aspenson and Hazary 58-63)

- "A heart attack occurs if the flow of oxygen-rich blood to a section of heart muscle suddenly becomes blocked. If blood flow isn't restored quickly, the section of heart muscle begins to die". (NIH)
- Heart failure is the condition that exists when the heart does not pump the way it is supposed to, so it fails to supply the blood required by the body. "Heart failure is a major health problem in the United States, affecting about 4.6 million Americans. About 550,000 new cases of heart failure occur each year. It is the leading cause of hospitalization in people older than 65". (Cleveland Clinic)
- "Pneumonia is an infection in one or both of the lungs. Bacteria, viruses, and fungi can cause pneumonia. The infection inflames your lungs' air sacs, and they may fill up with fluid or pus, causing symptoms such as a cough with phlegm, fever, chills, and trouble breathing". (NIH)

Hundreds of hospitals across the country will lose over $280 million in reimbursements (combined) due to high readmission rates during fiscal year (FY) 2013. The actual determination of these penalties was actually based on readmissions from July 1, 2008 to June 30, 2011. Administrators are paying very close attention to this legislation, especially since some facilities have already experienced reduced Medicare reimbursements.

The quality of service is certainly an issue (Boulding et al. 41-48), and many experts attribute this downgrade to the "brokenness" of the system and the enterprise in general (Friedman and Basu 225-240). These financial penalties and repercussions have roused healthcare entities, and they have shifted their gears from neutral to drive to construct strategies to address their readmission issues. A qualitative study conducted at 6 hospitals, with input from 12 hospital administrators, concluded that the use of prediction tools is a key strategic method for tackling readmission issues (Ahmad et al.). The ultimate goal of this study is to create one such prediction tool with “statistical teeth” to assist these healthcare institutions.

One might be tempted to say that a hospital can simply choose to not be associated with Medicare; however, it is not so easy for these institutions to simply detach themselves. Their very financial and operational structures are intertwined, and they are dependent on the funds obtained from Medicare. Administrators, and personnel alike, must act now.

The high readmission rate outlined in this policy is based on the patient being readmitted within 30-days of being discharged. There are a substantial amount of reasons to explain why readmissions occur, and quality of care tends to be a very popular culprit. There is the possibility that the patient did not get adequate treatment or the coordination of care and follow up was not sufficient. Furthermore, there are times when complications arise during treatment or the patient’s health may have taken an unexpected turn for the worse after being discharged. In fact, there is a possibility that the readmission is due to the patient’s own negligence. This project will not address all these issues, but will aim to help establish a basis for issues from the enterprise standpoint, i.e. what are key factors, at various points of the care process, that can lead to high readmission rates.

October 2012 was the month of enlightenment for over 2000 hospital facilities who received these penalties across the country, and they stand a chance of receiving higher penalties each ensuing year moving forward into the future if change does not occur (Hospital Case Management 18.9 129-139). Scores of hospitals in Texas were impacted, and that number can rise next year. The “doomsday” idea is that these same hospitals have a high likelihood of being penalized again, given that the timeframe for formulating and implementing resolutions can be extremely long.

1.2 Research Objectives

Research of hospital readmission rates has been ongoing for many years. As was previously mentioned, the purpose of this study is to look at the readmission problem from an enterprise and systems standpoint. Analyses will be done to explore and to gain some perspective of how system improvements could yield better results in the quality of care, and thus lead to reduced readmission rates.

Although it would be ideal to characterize and include all hospitals across the nation impacted by penalties, the focus will only be placed on the Texas hospitals that were penalized in this first wave of Medicare reimbursement cuts.

The objectives of this dissertation can be summarized in these main questions:

- DATA COLLECTION: Of the data available, what key determining characteristics or parameters can define the Texas hospitals that were penalized? Where do these characteristics fit in the overall enterprise or systems process view of healthcare services? The generic flow of a hospital system can be summarized as seen below. The data collection will be driven by this overall flow, and the parameters will be categorized according to the three key process steps.

The Flow of the System

- ANALYSES: Can a predictive model be established using statistical techniques to assist hospitals with determining their “penalty potential status”?

- ACCESSIBILITY: Can the statistical model be converted to a format that is accessible and interactive?

The greatest benefit from this project is for the hospitals to be able to apply the established model to their own operations and process flows for inpatient and outpatient services to assess potential and actual risk factors, and thus determine the likelihood of being penalized. Knowing where they stand will allow them to preemptively act to prevent possible Medicare penalties. All hospitals, and in particular, the hospitals that were impacted this year, will be actively looking for resolutions. This is an ideal time to perform a study such as this.

One key output of this research study is the establishment of a construct that can potentially lead to the development of a user friendly and interactive technological tool that is based on the established model. Hospitals interested in gaining more insight about their operations will find this gauge useful and can use it as a self-assessment tool throughout the fiscal year to make projections and any needed adjustments.

1.3 Limitations

Considering there are 178 hospitals in Texas that were penalized, it will not be possible to personally interview or survey all of them for this study. The challenge will be to get a representative sampling of the hospitals and obtain key information from them. Alternatively, in the absence of data, it is quite feasible to make good use of public information available. Access to hospital data will be a challenge due to the nature of these businesses that are highly regulated externally and internally.

Further limitations reside in the fact that data is not entirely exhaustive, so there will be some gaps in availability of information; however, as was previously mentioned, it will be essential to explore as many avenues as possible to get the data needed to conduct this research. The reliance on the healthcare databases available will be critical for searching and extracting key data related to this study.

CHAPTER 2

BACKGROUND

2.1 The Financial Impact of the Affordable Care Act of 2010

A significant part of the Patient Protect and Affordable Care Act of 2010 is focused on reducing costs associated with hospital readmissions. The healthcare facilities across the nation that contract with Medicare to provide acute inpatient services at their respective locations have to agree to accept predetermined payment rates for services rendered. "The inpatient hospital benefit covers beneficiaries for 90 days of care per episode of illness with an additional 60-day lifetime reserve. Illness episodes begin when beneficiaries are admitted and end after they have been out of the hospital or Skilled Nursing Facility (SNF) for 60 consecutive days (Centers for Medicare & Medicaid Services 10)".

The revenue received from Medicare is quite significant for these hospitals, and they depend on these funds to enable and sustain their operations. Unfortunately, as this particular legislation identifies, a guarantee of payment for services rendered does not guarantee top quality services. The national average for hospital readmission rates have lingered around 19% for many years, and now the Patient Protect and Affordable Care Act of 2010 made provisions to impact the financial bottom-line of hospitals – a clever and popular way to stimulate change (Rau).

It is estimated that approximately 20% (nearly 2 million) of Medicare beneficiaries (Trachtenberg and Ryvicker 645-651) return to the hospital for the same condition within a month of being discharged, and these expenses amount to billions in additional hospital charges, and to be more specific, to approximately $17.5 billion annually (Jencks, Williams, and Coleman 1418-1428). The first of these penalties to address these costs were enforced during the month of October 2012 in the form of withheld reimbursements, which amounts to over $280 million. Collectively, this is quite a significant loss and financial impact to hospitals. The Center for Medicare and Medicaid Services (CMS) is the organization responsible for dispersing and withholding reimbursements to hospitals, and the first wave of penalties were limited to a maximum of 1% of the total reimbursement due. Each year the penalty with increase a percent: 2% maximum in FY 2014 and 3% maximum in FY 2015. Hospitals have always been under huge pressures to prevent readmissions, but this negative consequence will serve to hasten their efforts to improve quality and explore better ways to have sustained positive patient results.

2.2 Penalties for 2012

The newness of the readmission penalty program is evident in the updates that have been made after the October 2012 penalties were imposed. There was a small reduction in the total number of hospitals being penalized. The initial amount of hospitals penalized was dropped from 2217 to 2213 for this initial round. Figure 2.1 graphically illustrates the distribution of penalty percentages by state, which was constructed by summing all the penalty percentage values for each state. New York received the highest total raw percent (max = 85%), and Vermont received the lowest total raw percent (min = 0.1%). Texas (in blue) was the second highest and obtained a total raw percent = 58%. The term “raw” is simply a summation of all penalties for each hospital.

In addition to the number of hospitals penalized, another adjustment was made in the total number of hospitals that were penalized at the full 1% rate – instead of the initially reported 307 hospitals; only 276 received the maximum penalty.

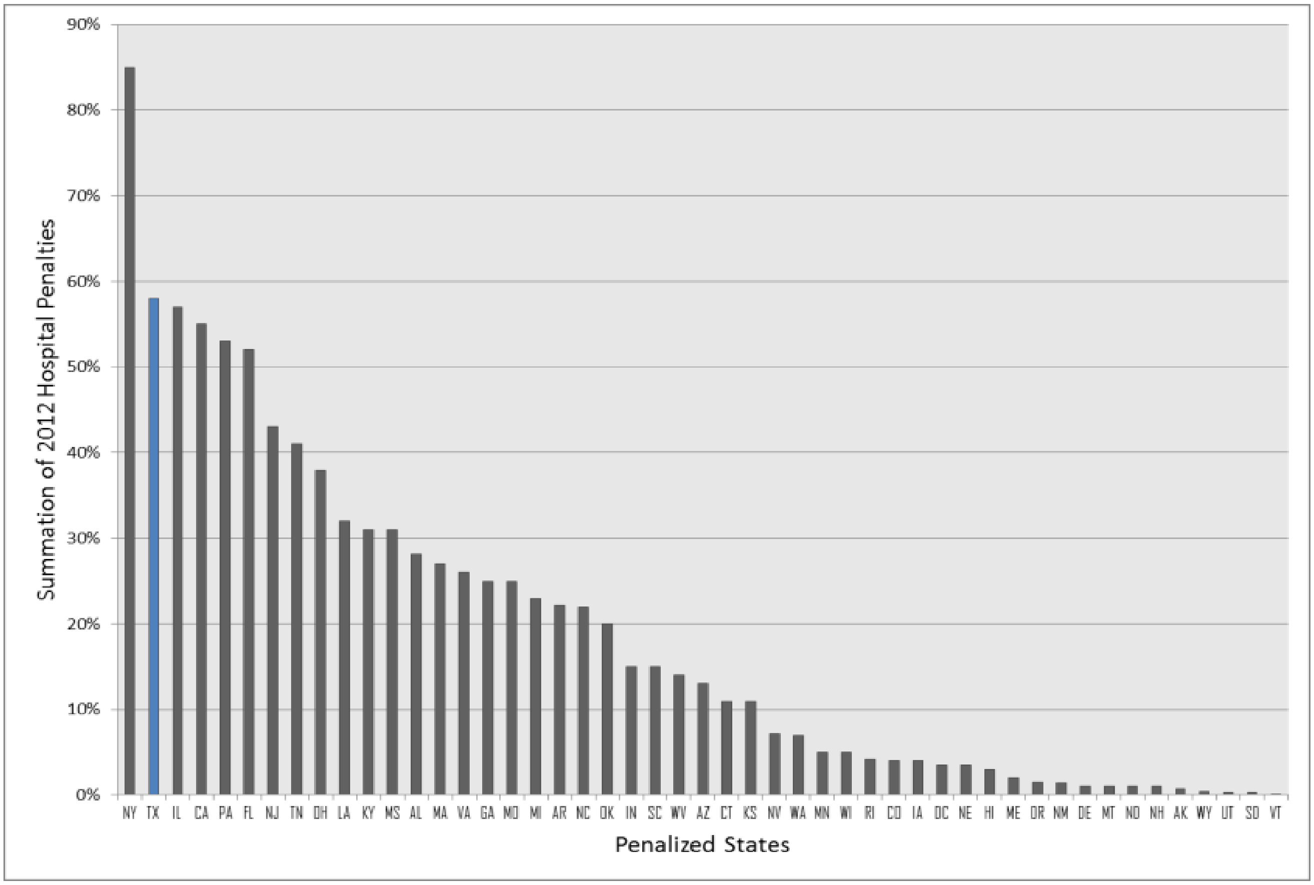


Figure 2.1: Summation of 2013 Medicare Penalties (%) for each Impacted State (Raw Penalty Sum per State) Data Source: Henry J. Kaiser Family Foundation, Kaiser News Network, 2013)

It is important to note that a few exemptions were made to the pool of hospitals for the hospitals in Puerto Rico were excluded entirely from this program. Furthermore, since the hospitals in Maryland are governed by a unique reimbursement arrangement, they were excluded from the first wave of penalty reviews as well.

There are a variety of health conditions that lead to the initial admission and readmission of patients, but as was mentioned before, Medicare is only focused on addressing the readmission rates for patients with the following conditions: heart failure, heart attack and pneumonia. The period of July 1, 2008 through June 30, 2011 was the timeframe that was used for determining the level of readmission rates for the first wave of penalties, and if the rates were deemed too high, the hospital was slated for penalties.

Hospitals are busy implementing resolutions to improve the quality of care and reduce readmission rates; however, it has become evident that it takes more than the hospital to make a dent in readmission rates, it will take action from the entire system or network of key participants; for examples, hospitals, patients, families, primary care physicians, pharmacy, nursing homes, outpatient and inpatient services and personnel (Birk 16-24). To make a significant change, solutions stemming from an enterprise or systems outlook have great potential, and needs to be seriously considered. Pockets of solutions or "Band-Aid" resolutions have been research, studied and implemented; however, the impact to the readmissions rates is still minimal. A system-wide scrub is essential for the revelation of underlying process issues that maintains the sub-par standards in quality and high readmission rates across the nation (Cykert 31-33).

2.3 Hospital Readmission Monitoring Rationale

The Center for Medicare & Medicaid Services used statistically formulated equations to determine the penalties. These formulas have specific input values that are based on many things, including data reported by individual hospitals and financial history tracked by Medicare.

“The CMS 30-day readmission measures assess a broad set of healthcare activities that affect patients’ well-being. Patients who receive better care, both during their hospitalizations and their transition to the outpatient setting will likely have improved outcomes, such as survival, functional ability and quality of life” (Quality Net).

The Department of Health and Human Services’ National Quality Strategy is focused on three key things: the improvement of health care quality, the health of the American population, and the reduction of healthcare costs (Quality Net). There are scores of other organizations that monitor the performance of hospitals, and collectively, all these programs do a great service. The availability of documented and validated performance and quality standards gives the patient information that will help them make informed decisions regarding their healthcare needs. Furthermore, access to information will enable patients to identify a facility that would be best suited for their immediate needs.

There are programs in place to reward hospitals for making great strides in improving quality and reducing costs. The incentives these healthcare facilities receive will in turn motive them to work even harder to bring more improvements to the operation.

The measuring and reporting of readmission rates will create incentives for hospitals and health systems to: “evaluate the entire spectrum of care that they and their affiliated providers furnish to patients, identify systemic or condition-specific changes that will make care safer and more effective, invest in interventions that reduce complications of care, better assess the readiness of patients for discharge, improve discharge instructions, reconcile medications, more carefully transition patients to outpatient care or other institutional care” (Quality Net).

It is a fact that we are living in the information age, and the access to information is really limitless. Our society expects to have answers for all their inquiries at their fingertips, and the monitoring of hospitals will help facilitate the healthcare decisions that are made on a daily basis.

2.4 Penalty Assessment Summary by State

2.4.1. Breakdown of All Hospitals Penalized

"Section 1886(d) of the Social Security Act (the Act) sets forth a system of payment for the operating costs of acute care hospital inpatient stays under Medicare Part A (Hospital Insurance) based on prospectively set rates. This payment system is referred to as the inpatient prospective payment system (IPPS). Under the IPPS, each case is categorized into a diagnosis-related group (DRG). Each DRG has a payment weight assigned to it, based on the average resources used to treat Medicare patients in that DRG". (Centers for Medicare & Medicaid Services)

The penalties the hospitals received varied across the board, and only the IPPS hospitals were impacted. See Table 2.2 to see the breakdown of penalties across state lines. The data is sorted on number of hospitals penalized per state (middle column), and California, quickly followed by Texas lead the pack of hospitals. There were 3104 hospitals that were reviewed for potential penalties, but only 2213 of them were actually penalized, and this count is based on updates that were made by Medicare in 2013. The graph reflects the 2012 initial data.

It is important to reiterate that Medicare's evaluation criteria was solely based on a hospital having at least 25 heart attack, heart failure or pneumonia readmission cases.

The average penalty assessed against the eligible hospitals was 0.31%, with a range of 0.00% to 0.68%. Interestingly enough, Idaho had 10 hospitals that were eligible for penalties; however, none were penalized (Kaiser).

Table 2.1: 2013 Medicare Readmissions Penalties by State (Data Source: Henry J. Kaiser Family Foundation, Kaiser News Network, 2012)

*NOTE: Adjustments were made to the total count of penalized hospitals – new count is 2213.

State	Total Hosp. Eligible for Penalty	No. of Hosp. Penalized	Avg. Penalty for Eligible Hosp.
California	273	197	0.21%
Texas	265	180	0.23%
New York	160	145	0.55%
Florida	161	131	0.34%
Illinois	127	112	0.47%
Pennsylvania	141	112	0.39%
Ohio	123	97	0.32%
Tennessee	95	75	0.45%
Georgia	106	73	0.25%
Alabama	92	65	0.32%
New Jersey	64	62	0.69%
Louisiana	74	60	0.44%
Virginia	73	59	0.36%
North Carolina	84	59	0.28%
Mississippi	60	55	0.53%
Kentucky	65	55	0.50%
Massachusetts	59	54	0.47%
Michigan	90	54	0.26%
Missouri	75	53	0.35%
Oklahoma	73	51	0.28%
Arizona	58	41	0.23%
Indiana	82	41	0.19%
Arkansas	43	37	0.53%
South Carolina	54	34	0.29%
Kansas	46	29	0.25%
Minnesota	49	29	0.11%
West Virginia	32	28	0.46%
Washington State	47	28	0.15%
Wisconsin	62	26	0.09%

Table 2.1 - continued

State	Total Hosp. Eligible for Penalty	No. of Hosp. Penalized	Avg. Penalty for Eligible Hosp.
Connecticut	31	23	0.36%
Colorado	42	20	0.10%
Nevada	21	17	0.36%
Iowa	33	16	0.13%
Nebraska	19	11	0.19%
New Mexico	29	11	0.06%
Oregon	32	11	0.05%
Maine	20	10	0.10%
Rhode Island	10	9	0.43%
Hawaii	14	9	0.24%
New Hampshire	13	8	0.09%
District of Columbia	7	6	0.52%
North Dakota	7	5	0.19%
Alaska	9	4	0.08%
Wyoming	11	4	0.04%
Delaware	5	3	0.21%
Montana	11	2	0.10%
South Dakota	13	2	0.02%
Vermont	6	2	0.02%
Utah	28	2	0.01%
Idaho	10	0	0.00%
GRAND TOTAL	**3104**	***2217**	**0.31%**

The state of California had the highest number (count = 273) of hospitals receiving penalties, followed by Texas with a count of 265. New York has the highest penalty average (0.55%) and result is not entirely surprising given the results that were noted in Figure 2.1. The graphical representation of the penalized hospitals is shown in Figure 2.2, and it is clear that California and Texas are the apparent outliers in this dataset, from the standpoint that they tower over the others. They both excel in bar height, when compared to the other states. Texas is shaded blue for ease of visualization, as it being the state this study is focused on.

2.4.2 Breakdown of Texas Hospitals Impacted

The state of Texas was second on list for Medicare penalties in terms of number of hospitals penalized. The breakdown for the Texas hospitals is shown in Table 2.2 and is illustrated in Figure 2.3. Of the total 315 hospitals listed, 265 were evaluated and met the criteria for penalties, but only 180 hospitals were actually penalized. Houston and Dallas were the regions with the highest amount of hospitals that were evaluated for penalties; however, we must consider that fact that these regions have more hospitals and more people, comparatively speaking, so it is expected to see their penalized counts on the high side.

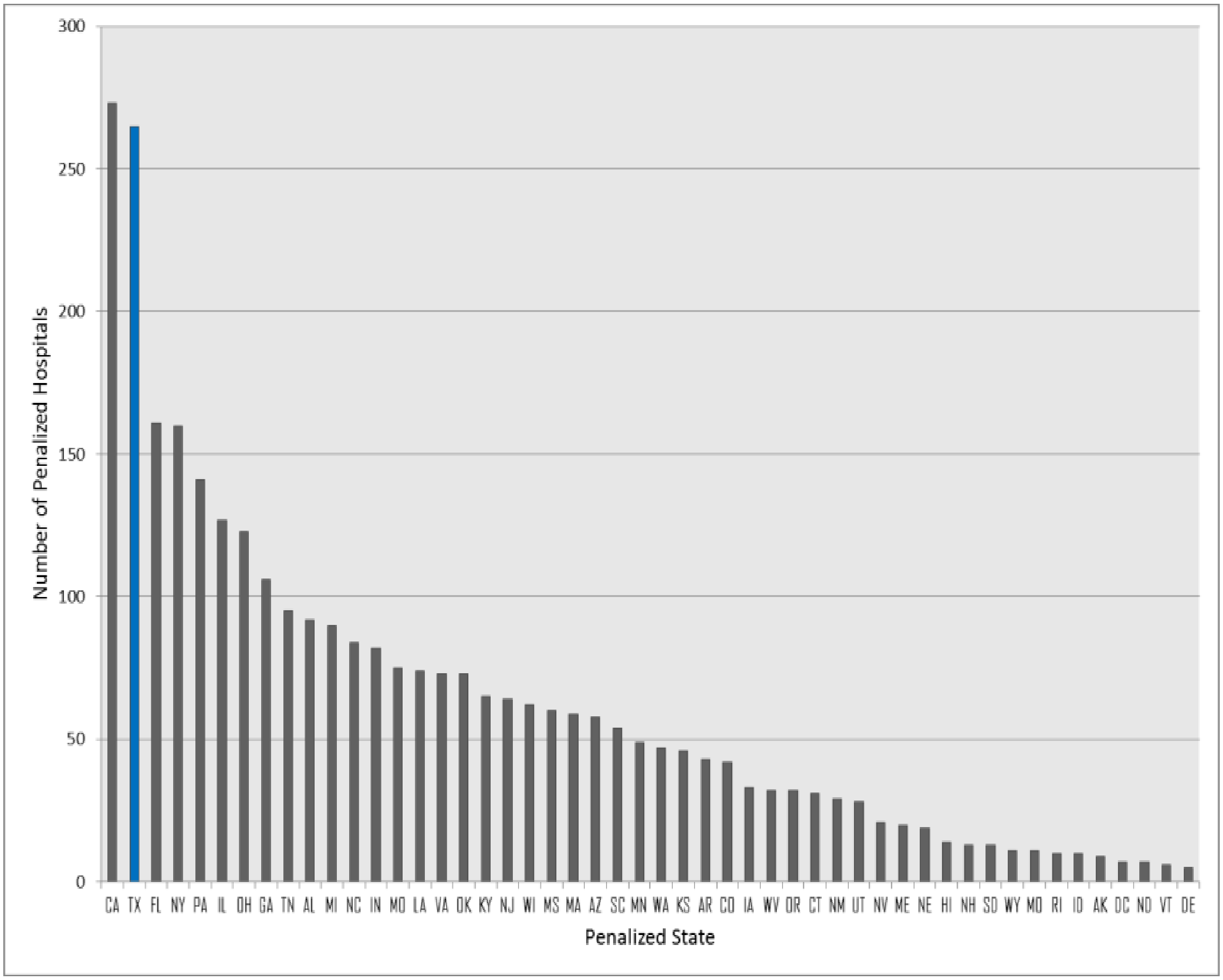


Figure 2.2: Total Number of Hospitals (by State) Penalized by Medicare (Data Source: Henry J. Kaiser Family Foundation, Kaiser News Network, 2012)

Table 2.2: Regional Breakdown of Texas Hospitals Slated for Penalty Evaluation. (Henry J. Kaiser Family Foundation, Kaiser News Network, 2012)

Hospital Region	Number of Hospitals
Houston, TX	69
Dallas, TX	65
Fort Worth, TX	25
San Antonio, TX	25
Austin, TX	18
Lubbock, TX	13
Tyler, TX	12
Abilene, TX	10
Amarillo, TX	9
Waco, TX	9
Beaumont, TX	7
Corpus Christi, TX	7
El Paso, TX	7
Wichita Falls, TX	7
Harlingen, TX	6
McAllen, TX	6
Odessa, TX	6
Bryan, TX	3
Longview, TX	3
Temple, TX	3
Victoria, TX	3
San Angelo, TX	2
GRAND TOTAL	**315**

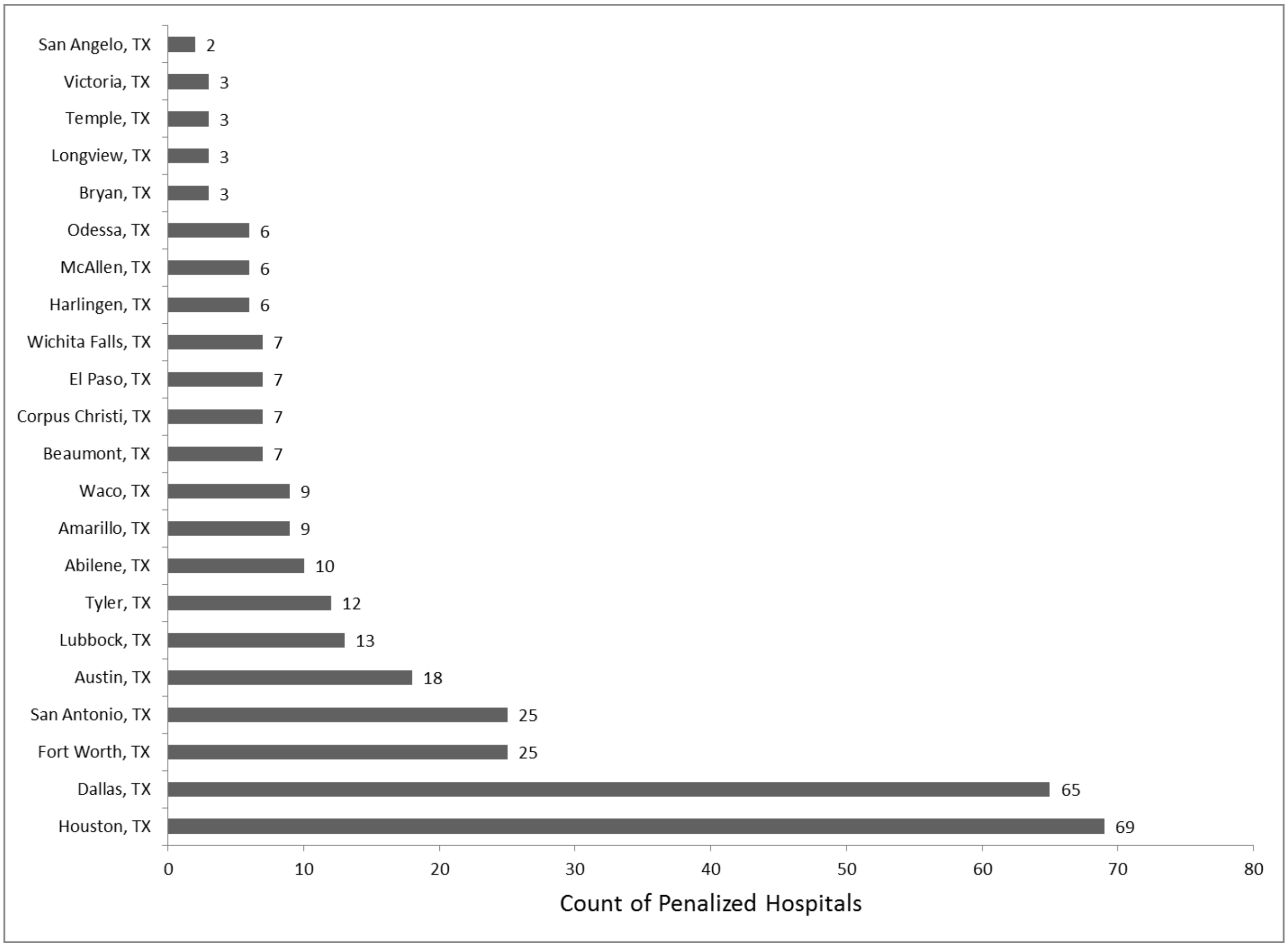


Figure 2.3: Graphical Distribution of Penalized Texas Hospitals by Region. (Henry J. Kaiser Family Foundation, Kaiser News Network

2.5 Inpatient to Outpatient Transition

"When patients move from the hospital to the next site of care—be it their home or a nursing home, rehabilitation facility, or hospice—they benefit from having a clear treatment plan they can understand and follow, providers who are aware of and able to carry out the plan, access to the right medications, and support services" (Silow-Carroll, S et al.).

The transition from being an inpatient to an outpatient is a very important and very critical adjustment that has to be made. The patient has to make an adjustment from being cared for, round the clock, to taking care of themselves, in some cases. Some are not so fortunate to have family members available to help out round the clock, and there are situations where the patient has no one to care for or check up on them at all. These are real circumstances and challenges patients face, and it can be quite a daunting task to leave the hospital, and then have to fend for yourself when you are still recovering.

A large degree of successful and swift recuperation from an illness or surgical procedure is dependent on how well the patient adheres to the discharge instructions – assuming these instructions were clear to begin with.

Hospital administrators have argued that Medicare penalties are not entirely fair due to the fact that they have no control of the patient's health and actions after being discharged. However, they must accept some responsibility due to the absence or inadequate coordination of care. The lack of a true healthcare delivery system, in mindset and structure, and the absence of the linkage of all key parties, has created a very disjointed health and wellness environment (MedPAC). Regardless of what the outcome of this debate is, the fact is that Medicare patients are being readmitted at a very high rate, and all parties tied to the care of these patients must collaborate to ensure the delivery, coordination and continuation of care is not interrupted (Goins 51-54).

The view of transition of care is truly extensive, and it is initiated with what occurs (or does not occur) in the hospital. While in the hospital, discharge instructions are given in various forms such as verbal and written. Then the question could be asked, are these instructions generic in nature, based on conditions, or are they truly tailored to the specific needs of the patient. It should be noted that patients may not understand 100% of the instructions, and then the obvious outcome is that they fail to do what is needed (Kripalani et al. 831-841).

The follow-up process after leaving the hospital is crucial. The patient needs to transition back to the care of their own primary care physicians, but at times, these appointments are not made in a timely fashion – the question then becomes: is the hospital checking on these patients as they should? Are they required to check on them after discharge? There are critical disconnects in the communication process that can be detrimental to the patient in the end. Medication prescriptions need to be filled, who will handle the order – the patient or the hospital? Does the patient have all needed medications? Has the primary care physician been informed of procedures done to the patient? There are many ways to break down the communication process - in content and delivery.

Some patients are discharged to sub-acute or long-term facilities. This certainly is a huge benefit in terms of continued care, but at times the facilities are not entirely informed of health history, current or ongoing issues and even discharge instructions.

In our very high technological world, facilities are resorting to automated home monitoring system to help coordinate care, and thus reduce readmissions and improve the outcomes for patients (Graham et al. 50-57). These methods are not entirely fail-proof, and they are not widely used. Tele-monitoring has great potential, but the technology has to be developed and integrated with regular operations. From a practical standpoint, if improvements are disjointed from the normal procedures or operating mode, most likely they will not become of the typical way of doing work, so there will always be issues with the process. "Well-executed communication among hospital providers, patients, and receiving providers at the time of hospital discharge contributes to better health outcomes and lower overall health care costs" (Voss et al. 1232-1237; Markley et al. E1-E11). The OUTPUT step covers the discharge aspects of addressing readmission.

The discharge activities actually should begin during the hospital stay. The patient should have a clear understanding of their health changes, and the actions that are needed to help them regain their health. Communication about the medication that is given to them while in the hospital, which potentially could be a medicine they have to use at home as well, will help them become acclimated to some kind of routine while in the hospital.

Training for recovery at home should begin in the hospital. If the patient is able to get comfortable with the various recovery activities before being discharge, naturally there will be a higher likelihood of being successful outside of the hospital setting.

CHAPTER 3

METHODOLOGY / LITERATURE SEARCH

3.1 Overview

The literature search was focused on exploring other relevant work done to address and explore the hospital readmission issue. Historically, re-hospitalization has been an issue, what has brought it to the surface now is the Medicare challenge to healthcare facilities and the curtailing of reimbursements. This body of knowledge will enable hospital administrators to evaluate their own facilities against the characterization of the 2012 hospitals that received penalties.

To gather information about the current status of hospitals and their readmission challenges, an extensive literature search was performed to gather insight on past related research on the topic. Accessing personal patient information online is practically nonexistent for obvious reasons, but there are healthcare databases on the internet that are quite useful for analytical purposes. Some of these databases were established in the spirit of transparency to enable patients and their families to make informed decisions about physicians and healthcare facilities. Furthermore, individual hospitals publish self-assessments and survey results on their corporate websites as well. The access to and compilation of needed healthcare data is key to this research.

The prime goal of the project is to gain an understanding of the Texas hospitals that received these penalties. Identifiable commonalities between hospitals are important elements to explore and will be highly suspect. The idea of a hospital system facilitated the establishment of a master process map. The overall operation flow amongst these hospitals, will lead to the identification of key parameters or variables that are common across the board. Data limitations will not allow us to make these evaluations from the hospitals standpoint, for the data used for some of the factors are from the patient standpoint – their experience during the hospital stay. The categorization of these variables into input-output terms will be the springboard for constructing the factors that play a direct role in hospital readmissions.

Many things need to be explored for the compilation of the key factors for the elevated hospital admission rates. The following section outlines the areas requiring exploration and the means through which the research and collection of data will occur.

Operations thrive on establishing, maintaining and enforcing processes and policies. The constant flow of work in an organized and consistent fashion ensures, to a large extent, that required tasks are being completed properly. The healthcare industry is no exception. Considering this industry is one of the fastest growing and oldest industries today, hospitals need to be sure their operations have robust processes in place, it is a matter of life and death – literally.

A top-level flow of a typical hospital process (see Figure 3.1) is illustrated below, and it highlights the overall concept of inputs and outputs. INPUTS in this study are specifically referring to the innate makeup of the hospital – those elements that are "natural"; such as number of beds, physical location, ownership, etc. – a full discussion of inputs is forthcoming. The INTERNAL OPERATIONAL PROCESSES are inclusive of activities required to get the patient admitted, the provision of inpatient services and transferred to the OUTPUTS phase, where the change is made to outpatient status.

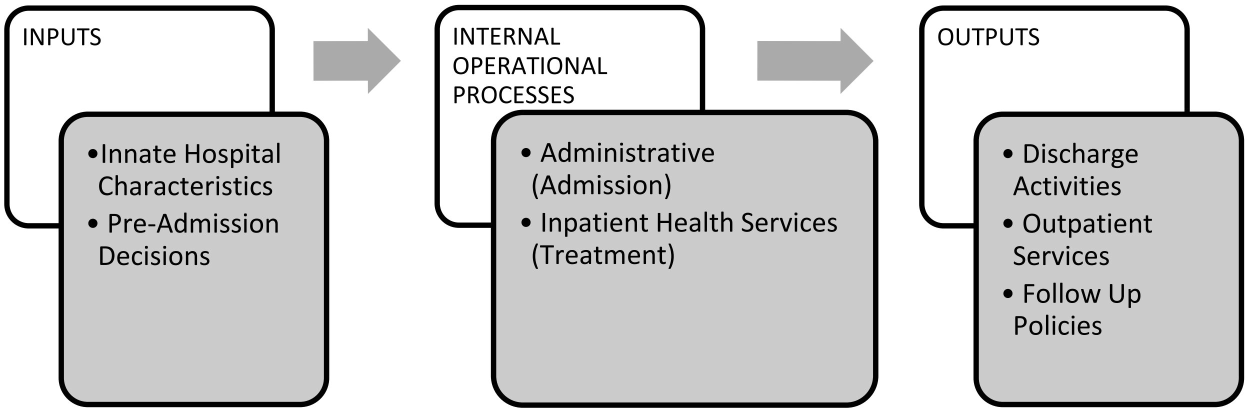


Figure 3.1: Defined Top Level Hospital Process Flow

3.2 Process Step #1 – Inputs

The literature review identified key innate hospital characteristics that are common to hospital facilities; namely, Size (number of beds), Number of Admissions, Ownership (Proprietary, Non Profit and Government), Environment Density (Urban vs. Rural location) Teaching Status (Teaching vs. Non-Teaching), (Jha, et. al.) and the Number of Personnel (Joynt and Jha 53-59). These input characteristics can play a role in the decision-making process for patients; hence, it is considered to be pre-admission entities. These factors become a part of the analysis to see if whether they have some statistical significance or impact on hospital readmission rates.

This analysis will yield the critical factors for the INPUTS (y_i) phase of the top level process map (see Figure 3.2). The actual Texas hospital data will be extracted from the industry databases: American Hospital Administration (AHA) Database and the American Hospital Database (AHD). The readmission administrative data for Medicare patients being readmitted to

Texas hospitals within 30 days of discharged will be obtained from the Center for Medicare and Medicaid Services (CMS) website.

$$y_i = x_1 + x_2 + x_3 + x_4 + x_5 + x_6$$

x_1	x_2	x_3	x_4	x_5	x_6
# of Beds	*Admissions*	*Environment*	*Ownership*	*Teaching Status*	*# of Personnel*

Figure 3.2: Input Predictors (x_i) for Regression

The formula in Figure 3.2, in a very generic way, represents the essence of the analysis – the goal is to construct an equation or model that has the ability to predict whether or not a hospital received penalties. Naturally, the dataset is limited to a certain timeframe; however an accurate and reliable model, with one set of data, can be a foundation for establishing models to predict if a hospital will be penalized in the future.

The response variable in this study is dichotomous in nature because there are only two possible states: Penalty and No Penalty. The analyses will be done with the Logistic Regression approach, specifically Binary Logistic Regression since there are two response states.

The Input variables are categorical and continuous. Two different approaches will be taken and are described by the following two formats:

- Format #1 - the first regression will be run with a combined predictor variable format with both categorical and continuous data.

- Format #2 - the second approach will be to categorize the covariate data into suitable sub-groups and run the regression with all categorical predictors.

The format that yields the highest number of significant predictors will be the format of choice, and that particular format will be used to run the final regression, which will be inclusive of all significant factors from the three top level processes.

The six predictors for the INPUT process step are listed in Table 3.1. The data types are also displayed to show what the factor level definitions and types will be for the two different formats that will be evaluated.

Categorical data are not numerical values, but rather data that can be divided into groups such as color, age and sex. Numerical data can be categorized if logical groupings of data ranges are established. For the ease of they analysis, the categories will have be to identified somehow for referencing purposes.

Table 3.1: Breakdown of Input Predictors for Analyses by Formats

PREDICTOR NAME	DATA TYPE	NUMBER OF FACTOR LEVELS (FORMAT #1)	NUMBER OF FACTOR LEVELS (FORMAT #2)
Number of Beds (x_1)	Continuous (Format #1) Categorical (Format #2)	N/A	4
Admissions (x_2)	Continuous (Format #1) Categorical (Format #2)	N/A	4
Density (x_3)	Categorical	2	2
Ownership (x_4)	Categorical	3	3
Teaching Status (x_5)	Categorical	2	2
Number of Personnel (x_6)	Continuous (Format #1) Categorical (Format #2)	N/A	4

3.3 Process Step #2 – Internal Operational Processes

The INTERNAL OPERATIONAL PROCESSES (y_p) is the second top level step in the process map and the overall hospital system – as defined by this study. As indicated in Figure 3.1, this step comprises the admission procedures and inpatient services and other key related things. Without looking specifically at the patient, the goal here is to identify elements from with-in the hospital operations that could impact readmissions.

The key elements that will be analyzed for this process step are: Registry participant status, Communication ranking, Quality ranking, Timely and effective care, Medicare (MDC) volume, and Medicare Payment Index (Epstein, Jha, and Orav 2287-2295; Palmer Jr. et al. 1318; Lemieux et al. 96-104). These crucial data points are collected on a periodic basis and convey a great deal of information about the reality and perceptions of hospital operations as they related to the staff and procedures. This analysis will yield the critical factors for the PROCESSES (y_p) step in the top level process map (see Figure 3.3).

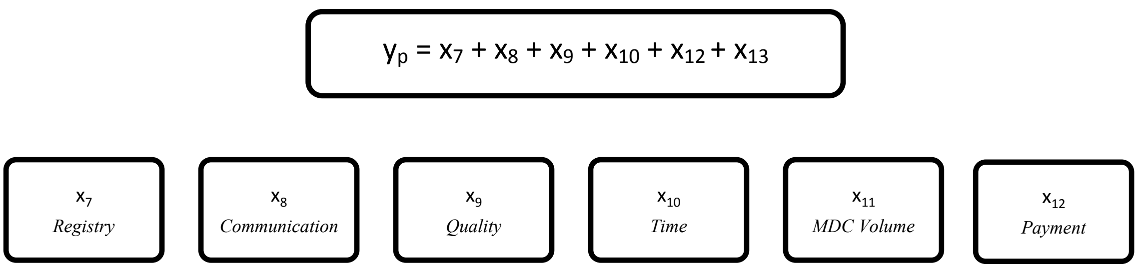


Figure 3.3: Operations Predictors for Regression

The Agency for Healthcare Research and Quality (AHRQ) website has several databases and compilations of data that will be utilized for obtaining details about these factors. Furthermore, the U.S. Department of Health and Human Services maintains a special database named “Hospital Compare” that will be used for extracting the needed data as well.

The actual Texas hospital data will be extracted from the industry databases: American Hospital Administration (AHA) Database and the American Hospital Database (AHD). The readmission administrative data for Medicare patients being readmitted to Texas hospitals within 30 days of discharged will be obtained from the Center for Medicare and Medicaid Services (CMS) website.

Again, the response variable is binary in nature because since there are two states: Penalty and No Penalty. The analyses will be done using the Binary Logistic Regression techniques since there are two response states.

The six general predictors for the PROCESS step have multiple levels. A snapshot of the levels for each factor is summarized in Table 3.2. The discussion of these factors is available after the table and will establish an understanding of their importance to the internal operations process step.

To ensure meaningful results are generated, it is important to select factors that are common across all hospitals. Key healthcare databases document this information for all hospitals, which is a part of the measurement reporting process of each hospital and critical to the transparency initiative. This information is publicly available to assist patients in their healthcare and health services decision-making process.

Just like the Input variables, the Operations predictor variables are categorical and continuous. The six predictors for the Operations process step are listed in Table 3.2. The data types are shown, and there is one categorical data set - Registry. Subgroups will be created in a variety of ways for the continuous data to determine the best format to yield the most significant predictors.

Table 3.2: Operations Predictors for Analyses

PREDICTOR NAME	DATA TYPE	NUMBER OF FACTOR LEVELS
Registry (x_7)	Categorical	5
Communication (x_8)	Continuous	N/A
Quality (x_9)	Continuous	N/A
Time (x_{10})	Continuous	N/A
MDC Volume (x_{11})	Continuous	N/A
Payment (x_{12})	Continuous	N/A

3.3.1 Discussion of Operations Predictor Variables

The selection of predictor variables for operations step was highly dependent on the information available in the public domain. The following discussion expands on the variable itself and the rationale on using it in the analyses.

- Registry Participant: Registries help hospitals collect and analyze data and help hospitals improve the care they provide. If a hospital is an active participant in these registries, it is a clear indication that they are interested in making improvements at their facility. A hospital that is committed to quality will do whatever it takes to reveal their initiatives and progress. This commitment to quality will be drilled down through the ranks of the facility (Granan et al.).

  Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) is an annual survey that is given out to random patients across the nation to rate their hospital stay. Response data on communication and quality is collected from these surveys each year.

- Communication: This factor is important because providing and following instructions is crucial to a patient staying out of the hospital. If the doctors and nurses fail to communicate, or fail to communicate effectively, in a manner that could be understood, then the patient will not know much about the care being received or what is required of them when they are discharged. Communication is the transfer of information from one person to another, and the physical and mental state of the patient has a tremendous impact on their ability to process and understand the information that is being conveyed.

- Quality: From a quality perspective, the patients get an opportunity to rank their overall stay, which covers the entire experience at the hospital. The recommendations they would give or not give to family or friends, with respect to the hospital, speak volumes on the quality of service received. The quality ranking is all-encompassing, for it sums up a patient's viewpoint of the hospital.

- Time: The time hospital personnel takes to respond to the needs of the patient is a matter of life and death; furthermore it can play a critical role in whether or not that patient has to be re-hospitalized. Is the nurse and doctor spending enough time with the patient? Time translates to communication…it will be expected that a decrease in time spent visiting the patient will render a decrease in communication, or vice versa.

- Medicare Volume (MDC): Given that the Medicare patients are served at reduce payment rates, compared to patients insured by other companies, it is imperative to understand whether or not the amount of Medicare patients in the hospital has an impact on the quality of service they receive the first time around, which may require them to be readmitted to recoup costs. This is a sensitive category, but it must be analyzed.

- Payment Index: This category is similar to Medicare Volume. The question becomes whether or not money plays a factor in hospital readmissions. The payment element being examined here is the ratio of Medicare payments to operational revenue – will be treated like an index. It is a well-known fact that Medicare represents a significant part of the budget for most of these hospitals, and if Medicare was to stop paying them, they probably would have to close the doors of the hospital.

The factors for the operations process step will be carefully examined for statistical significance. Some of these parameters have a direct impact on a patient being able to get the service they need while in the hospital; furthermore, some of them have an indirect impact on the kind of services that are provided in the inpatient setting.

3.4 Process Step #3 – Outputs

The OUTPUT PROCESS step (y_o) is the third top level step in the process map that was defined in this project. This step is where the planning occurs for transitioning the patient from inpatient to outpatient status. Discharge data is limited for this process step – there is only one factor available for this process step, and it is continuous in nature.

The analysis for this process step also focused on the compiling the transition methods of various hospitals. There are many hospitals with outstanding discharge procedures. These methods ensure that there is a clear transition plan for moving the patient from inpatient to outpatient status. The ability to understand and adhere to discharge instructions is extremely important and will certainly help the patient stay out of the hospital.

The healthcare databases previously mentioned captures the communication aspects of discharging the patient and will serve as the factor for this process step.

3.5 Research Hypothesis

Independent Variables: Predictors outlined in process steps.

Dependent Variable (Response): Penalty/No Penalty

Null Hypothesis: None of the independent variables affects the probability that the dependent variable will be Penalty or No Penalty. This implies that $ß_1$, $ß_2 \ldots ß_n$ are all zero and that only $ß_0$ differs from zero.

(H_0): $\beta j = 0$ for all j

Alternative Hypothesis: At least one of the independent variables affects the probability that the dependent variable will be Penalty or No Penalty. This implies that $ß_1$, $ß_2 \ldots ß_n$ are not all zero.

(H_1): $\beta j \neq 0$ for at least one j

Research Hypothesis: The dependent variable is more likely to be “Penalty” for some values of the independent variables than for others. This implies that some βj differ from zero.

Rejection Criteria: There are no significant factors to predict Penalty or No Penalty.

CHAPTER 4

ANALYSES: INPUTS, OPERATIONS, OUTPUT

4.1 The 80%-20% Split of the Hospitals

The intent of this study is to understand the fundamental reasons why some hospitals were penalized and some were not. There is great technical and analytical merit in performing analyses on the Texas hospitals that were not penalized as well, for it becomes a point of reference for discussing the analyses of the hospitals that were penalized.

Many hospitals in Texas were penalized, and to be exact, 180 hospitals experienced the first wave of the now ongoing Medicare penalties. Out of the total Texas hospitals that were penalized, only a portion of that total amount could actually be used in this research study. One prime goal of the data collection process was to obtain a complete record, inclusive of all variables, for each hospital. Unfortunately, a complete record was not obtainable for some of the hospitals, bringing the "Penalized Hospitals" list down to 168, which represents 94% of the total amount of penalized hospitals from the state of Texas.

To facilitate the model formation and validation processes, the hospital dataset for "Penalized" and "Not Penalized" was randomly sub-divided into 80% / 20% subgroups. Eighty percent of the data, from both groups of data was reserved for model construction, and twenty percent of the data was reserved for the model validation process. Two-hundred and ninety hospitals are referenced in this study and Table 4.1 breaks down the sample size of each sub group.

Table 4.1: Model Formation and Model Validation Sample Sizes

TEXAS HOSPITAL BREAKDOWN			
Amount Slated As Suspect		*Amount Evaluated*	
315		265	
Amount Penalized		*Amount Not Penalized*	
180		137	
Penalized (168 Hospitals) *(# Used in Study)*		Not Penalized (122) *(# Used in Study)*	
Model Formation	*Model Validation*	*Model Formation*	*Model Validation*
134 (80%)	34 (20%)	98 (80%)	24 (20%)

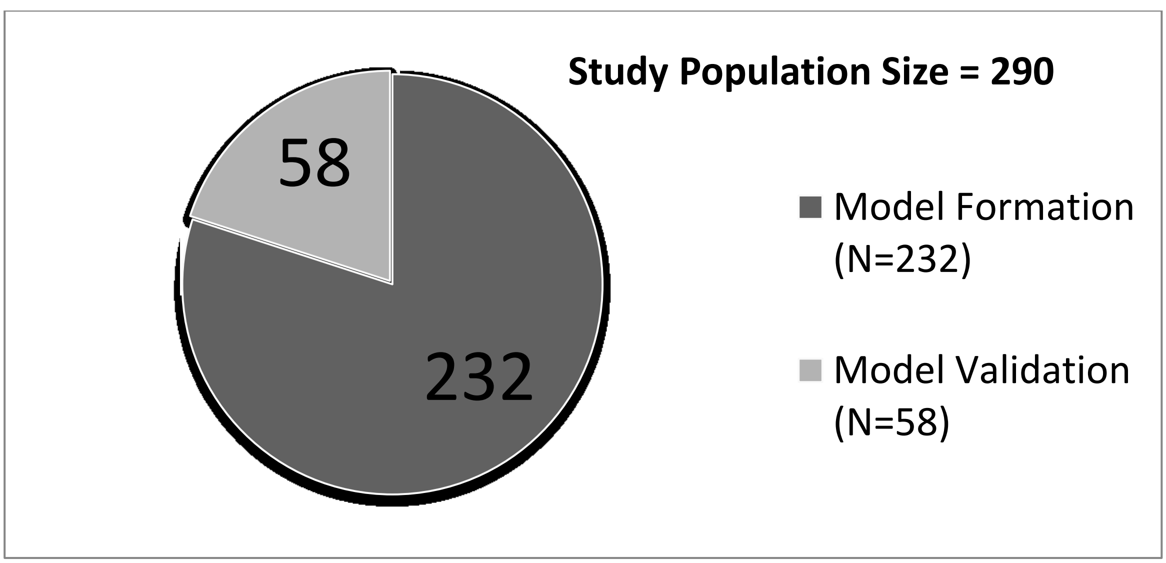


Figure 4.1: Sample Sizes

4.2 Analyses of Categorical Input Process Parameters – RAW DATA

The Input Process step accounts for six key elements that are innate to hospitals in general. Some of these things can change, but they seldom do. Density or Environment, Ownership, Teaching Status, Number of Hospital Beds, Number of Staff and Hospital Admissions all comprise the input process. The following preliminary analyses will serve as a basis for understanding the nature of these hospitals as they relate to the fundamental characteristics on which they were established.

4.2.1. Density of Population (Environment) Analysis

The population density factor refers to the kind of environment the hospital is physically located in. The two classifications for this factor are Urban and Rural. For clarity sake, an urban environment refers to those societies that are located in the cities or towns.

The population densities (people / area ratio) of urban environments are comparatively high. These environments will have more service operations available for their occupants. You will find a larger variety of hospitals, restaurants, schools and churches.

Rural environments are outside of the urban city areas, and they tend to have fewer people residing there, so the population densities are considerably smaller than urban areas. The comparatively lower people/area ratios leads to a fewer service operations – it just does not make good business sense to have huge operations in areas where the market is small. In light of this, you will have very limited eating options and even healthcare facilities.

In Figures 4.2 and 4.3, the graphical breakdown for these two environments, for both the penalized and non-penalized hospitals, is shown. Of the hospitals receiving no penalties, approximately 77.6% were in urban environments and 22.4% were in rural locations. About 64.9% of the hospitals that were penalized were located in the urban areas and 35.1% of them were located in the lightly populated rural environments.

The fact that there are more hospitals located in the urban areas will justify why the percentage of hospitals being penalized is higher than the rural areas. More hospitals in an environment that is heavily populated will lead to high admissions and naturally, higher read-missions. The amount of admissions in the urban areas is much higher when compared to the rural areas, so it is expected that the number of penalized hospitals will be higher as well.

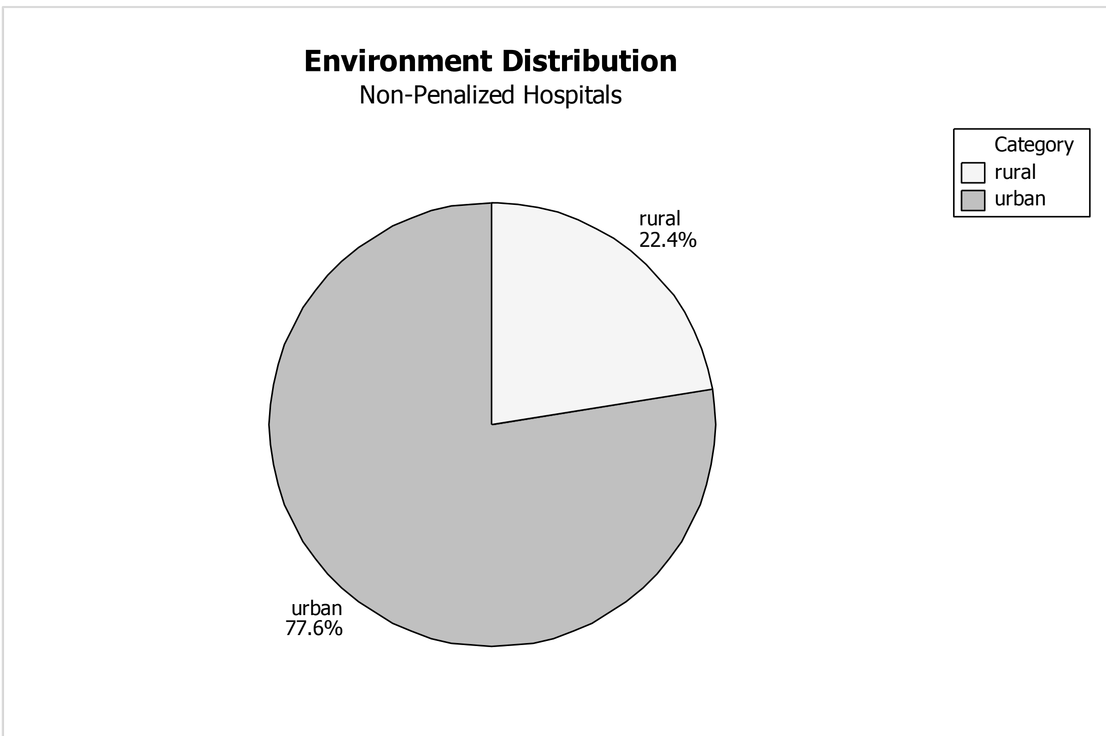


Figure 4.2 – Environment Proportion for Hospitals Not Penalized

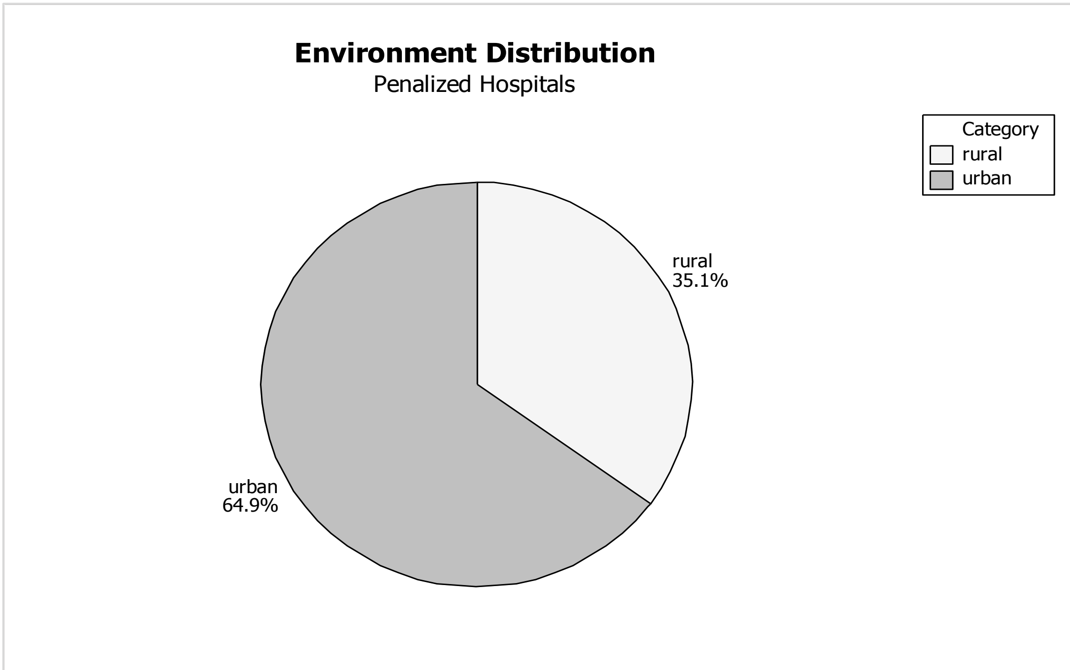


Figure 4.3 – Environment Proportion for Hospitals Penalized

4.2.2. Ownership Analysis

In general, the management and ownership of hospitals falls into three main categories: Proprietary, Government and Non-Profit.

- Government-Owned Hospitals: "Public nonprofit hospitals are owned by a governmental entity at the federal, state, or local level to serve diverse constituents, including the military, rural residents, the poor, and the uninsured" (Baker).

- Proprietary Hospitals: "Private for-profit hospitals are owned by private investors to make profits by serving the paying patients" (Baker).

- Non-Profit: "Private nonprofit hospitals are owned by a voluntary board of trustees to provide care for paying patients and charitable service to the poor" (Baker).

Hospital ownership is very dynamic, for there are closures, mergers and acquisitions. The administrative and management structures are going to be very different across the three types, but there will be a few commonalities. There is no surprise that quality and performance will vary across the board; hence it is imperative to include ownership as a predictor to be evaluated in this study. The distribution of ownership status in Figures 4.4 and 4.5 gives a clear view of how each hospital type was impacted by the first wave of readmission penalties.

The pool of non-profit hospitals received the most penalties with a percentage of 42.5%, followed by the proprietary with hospitals with 36.6%, and bringing up the rear are the volunteer hospitals with 20.9%.

Interestingly, Figure 4.4, which shows the distribution of hospitals that were not penal-

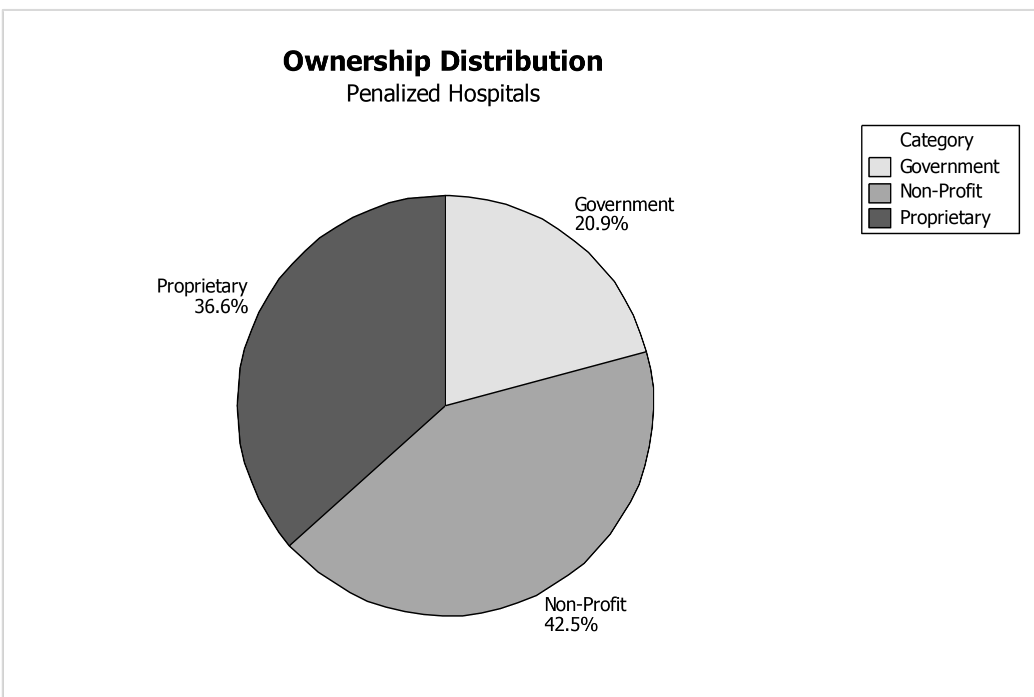


Figure 4.4 – Ownership Proportion for Hospitals Penalized

ized, actually had the reverse effect. The proprietary hospitals held a commanding lead with 52% of them not being penalized, followed by the nonprofit hospitals with 31.6% and lastly the government hospitals with 16.3%. In both charts, it is evident that the government run hospitals were the smallest pool of hospitals being penalized and not being penalized with 20.9% and 16.3% respectively.

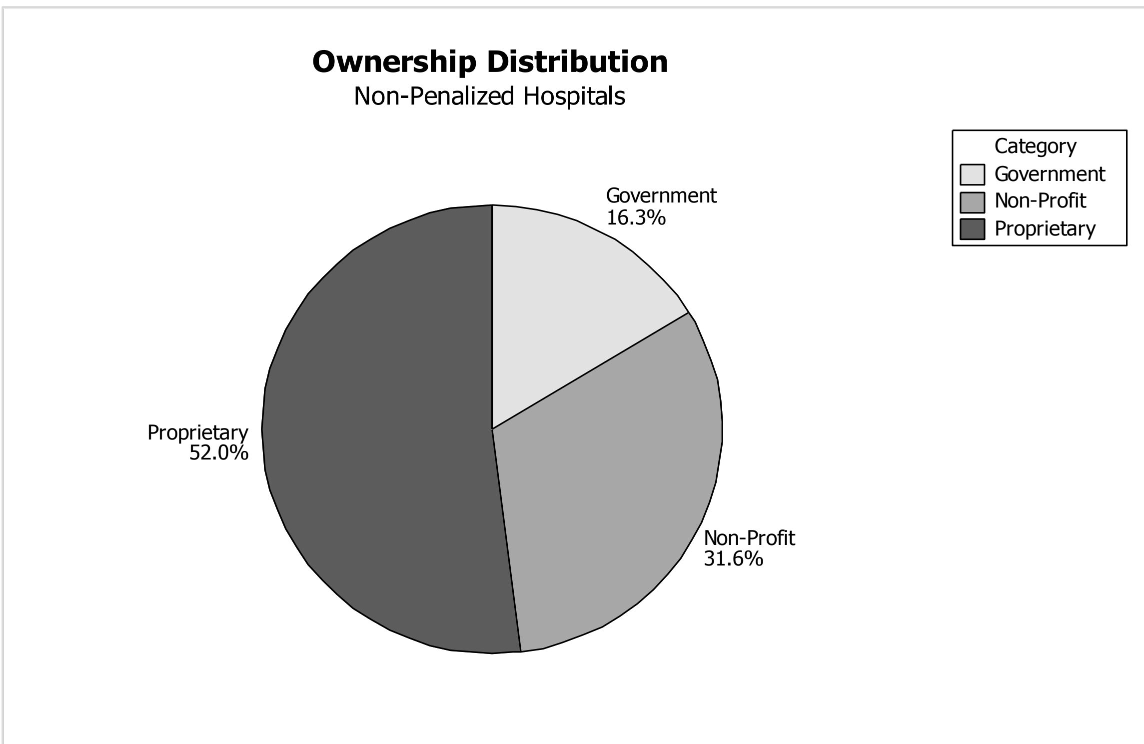


Figure 4.5 – Ownership Proportion for Hospitals Not Penalized

4.2.3. Teaching Status Analysis

Medical school and clinical activities for people pursuing a health-related career path will occur in the hospitals. This is on the job learning that is absolutely critical for the acquisition of knowledge. Some hospitals across the nation are classified as teaching hospitals, for their hallways and operating rooms are filled with a large proportion of students. These students need the direction of doctors and nurses.

The quality of care and overall operations and policies will be different; some may even venture to say that the function of teaching, undertaken by the hospital staff, may serve to be a distraction from their ability to perform their regular hospital roles at top quality. Some extend their belief that the direct patient care is jeopardized. (Grosskopf)

There are more non-teaching hospitals than teaching hospitals across the nation, so the teaching status distributions are not entirely surprising. As indicated by Figure 4.6, only 17.9% of the hospitals penalized were teaching hospitals greatly contrast by the 82.1% of the penalized hospitals being non-teaching facilities.

The huge gap between these percentages could simply be attributed to the fact that there are more non-teaching hospitals than there are teaching ones. It begs the question however – are the teaching hospitals, with the additional rigor of policies due to having students around, contribute to more oversight and better quality? It is more feasible to expect students to be more attentive to the details of their job, leading to satisfied patients. It is expected that since they are in the learning mode, that they would most likely go above and beyond the call of their training to satisfy their patients and impress their supervisors.

Figure 4.7 shows that 24.5% of the hospitals not penalized were the teaching hospitals, and the large percent of the hospitals penalized were non-teaching facilities with a value of 75.5%. Again, it is expected that the big gap in percentages is most likely due to the fact that there are fewer teaching hospitals.

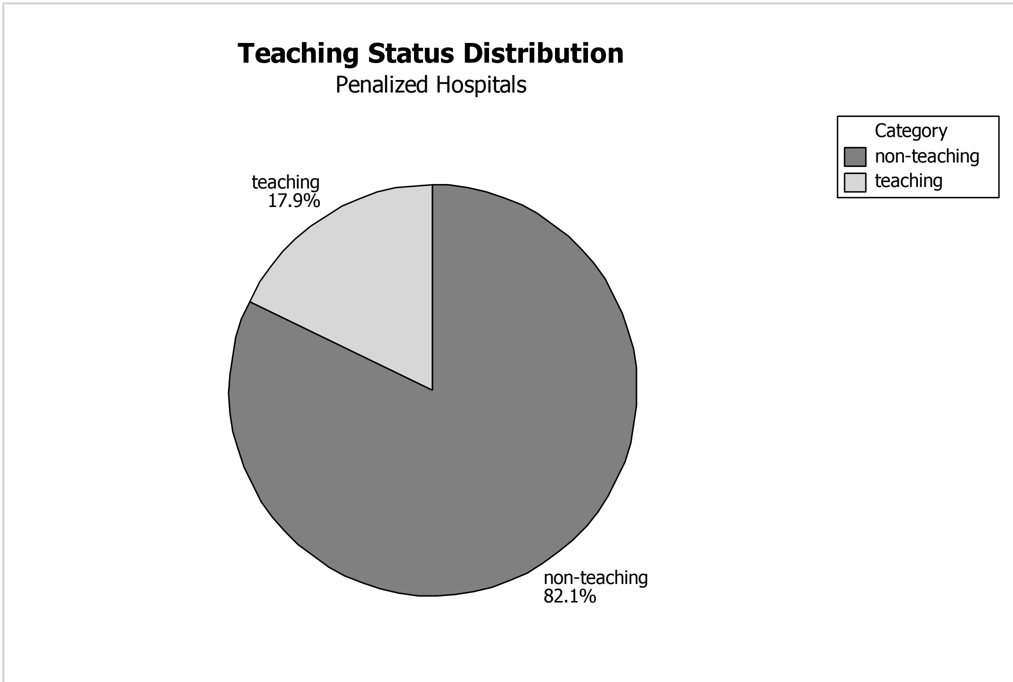


Figure 4.6 – Teaching Status Proportion for Penalized Hospitals

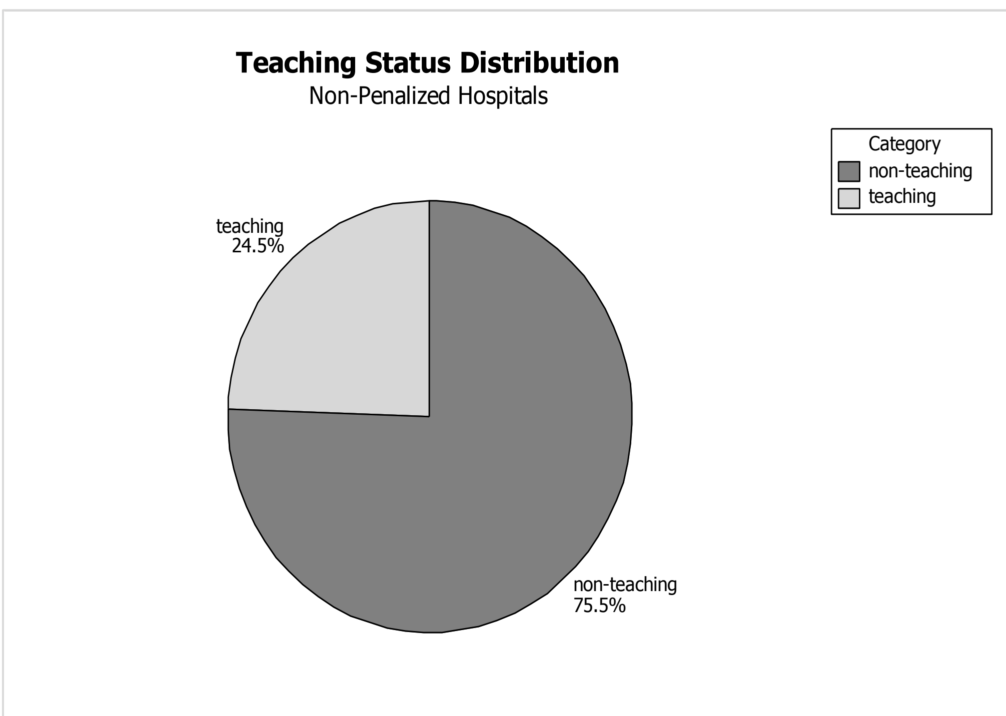


Figure 4.7 – Teaching Status Proportion for Hospitals Not Penalized

4.2.4. Summary of Categorical Data from Input Process

The previous analyses were focused on the categorical data from the Input process step. They give a clear representation of the percentage distribution of the input characteristics that were present in the hospitals that were penalized, and Figure 4.8 summarizes the overall results for these analyses.

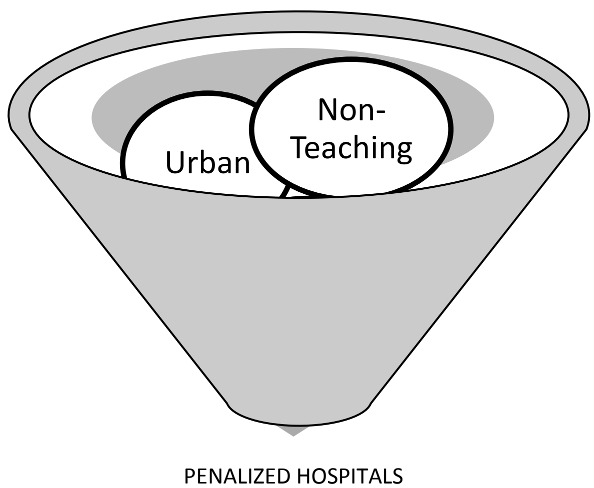


Figure 4.8 – Collection of Categorical Input Predictors with Highest Percentages

From the categorical standpoint, the hospitals that received the majority of the penalties were located in the city, they were non-teaching facilities and their ownership was primarily non-profit. At this point, these predictors are highly suspect and will be further analyzed using statistical tools.

4.2.5. Categorical Data – Chi Square Test

4.2.5.1 Chi Square Test for Teaching Status

The performance of the Chi Square at this point is to statically prove or disprove the observed results. The Chi Square test determines if there is statistically significant difference between the levels for each predictor. The statistical analysis for Teaching is based on the contingency summary in Table 4.2. There were a total of 60 teaching hospitals and 230 non-teaching hospitals, a range 170 shows there is a huge difference in the amount of hospitals that are utilized to instruct students in the healthcare professional.

Chi Square Test

H_0 = Penalty Status is Independent of Teaching Status (No Relationship)

H_1 = Penalty Status is Dependent on Teaching Status (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

Table 4.2: Contingency Table for Teaching Status

Classification of Sample of Teaching Status by Penalty Status (Penalty, No Penalty)		Teaching Status		Total
		Teaching	Non-Teaching	
Penalized?	Yes	34	134	168
	No	26	96	122
	Total	60	230	

** TEST RESULTS **

Chi-Square Test: Teaching, Not Teaching

	Teaching	Not Teaching	Total
1	34	134	168
	39.20	128.80	
	0.690	0.210	
2	36	96	132
	30.80	101.20	
	0.878	0.267	
Total	70	230	300

Chi-Sq = 2.045, DF = 1, <u>P-Value = 0.153</u>

Test Conclusion: ($p = 0.153$, $p > 0.05$) - no evidence exists for association between Teaching Status and Penalty Status.

4.2.5.2 Environment Status - Chi Square Test

The contingency summary for environment is shown in Table 4.3. There were a total of 209 urban hospitals and 81 rural hospitals, with a range 128 - again, a very large gap between the two groups. The penalties were higher for the urban hospitals, with a count of 117 urban hospitals being penalized, compared to the 51 rural hospitals that were penalized.

Chi Square Test

H_0 = Penalty Status is Independent of Environment (No Relationship)

H_1 = Penalty Status is Dependent on Environment (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

** TEST RESULTS **

Chi-Square Test: Urban, Rural

	Urban	Rural	Total
1	117	51	168
	121.08	46.92	
	0.137	0.354	
2	92	30	122
	87.92	34.08	
	0.189	0.488	
Total	209	81	290

Chi-Sq = 1.168, DF = 1, <u>P-Value = 0.280</u>

Conclusion: ($p = 0.280$, $p > 0.05$) - no evidence exists for association between Environment and Penalty Status.

Table 4.3: Contingency Table for Environment

Classification of Sample of Environment Status by Penalty Status (Penalty, No Penalty)		Environment Status		Total
		Urban	Rural	
Penalized?	Yes	117	51	168
	No	92	30	122
	Total	209	81	

4.2.5.3 Chi Square Test for Ownership Status

The contingency summary for ownership status is shown in Table 4.4. There were a total of 123 Proprietary, 108 Non-Profit and 59 Government hospitals. The range between propriety and the Non-Profit hospitals is 15, which is comparatively small when you consider the range for Propriety and Government, which is 64. The gap between Non-Profit and Government is 49. The penalties for each type for Non-Profit, Proprietary and Government in descending order are 69, 64 and 35 respectively.

Chi Square Test

H_0 = Penalty Status is Independent of Ownership Status (No Relationship)

H_1 = Penalty Status is Dependent on Ownership Status (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

** TEST RESULTS **

Chi-Square Test: Proprietary, Non-Profit, Government

	Proprietary	Non-Profit	Government	Total
1	64	69	35	168
	71.26	62.57	34.18	
	0.739	0.662	0.020	
2	59	39	24	122
	51.74	45.43	24.82	
	1.017	0.911	0.027	
Total	123	108	59	290

Chi-Sq = 3.376, DF = 2, P-Value = 0.185

Conclusion: (p = 0.185, p > 0.05) - no evidence exists for association between Ownership Status and Penalty Status.

Table 4.4: Contingency Table for Ownership

<table>
<tr><th colspan="2" rowspan="2">Classification of Sample of Ownership Status by Penalty Status (Penalty, No Penalty)</th><th colspan="4">Ownership Status</th><th rowspan="2">Total</th></tr>
<tr><th colspan="2">Proprietary</th><th>Non-Profit</th><th>Government</th></tr>
<tr><td rowspan="2">Penalized?</td><td>Yes</td><td colspan="2">64</td><td>69</td><td>35</td><td>168</td></tr>
<tr><td>No</td><td colspan="2">59</td><td>39</td><td>24</td><td>122</td></tr>
<tr><td colspan="2">Total</td><td>123</td><td>108</td><td>59</td><td></td><td></td></tr>
</table>

4.2.5.4 Chi Square Test Summary

The categorical data analyses for the Input process step revealed some important things. As was previously mentioned, the observations from the pie charts revealed that the hospitals that are urban, non-teaching and non-profit had more penalties assessed against them. It would be logical to assume that there would be some statistical significance to support these observations, especially considering the large disparities between the overall distributions of the penalties. However, the Chi-Square analyses showed that there is no statistical evidence that the categorical Input predictors will have an impact on the determination of penalties, i.e. these predictors will not contribute to the model for predicting a hospital being penalized.

4.3 Analyses of Continuous Input Process Parameters – RAW DATA

4.3.1 Number of Hospital Beds Analysis - Continuous Data

The number of penalized hospitals being used in this analysis, as was previously mentioned is 134. Within this pool, the average number of beds in the hospitals is 180.63, with a standard deviation of 172.44, see Figure 4.9. There is a tremendous spread of values, which is not surprising due to the varying sizes of hospitals being used in this analysis. The Anderson-Darling Normality test was computed at the 0.05 significance level, and the resulting P-Value, which is less than 0.05, clearly indicates that the data is not normal. The majority of the hospitals that were penalized were in the 500 beds or less range, which led to the classification of hospitals with bed counts greater than 500 registering as outliers in the box and whisker plot.

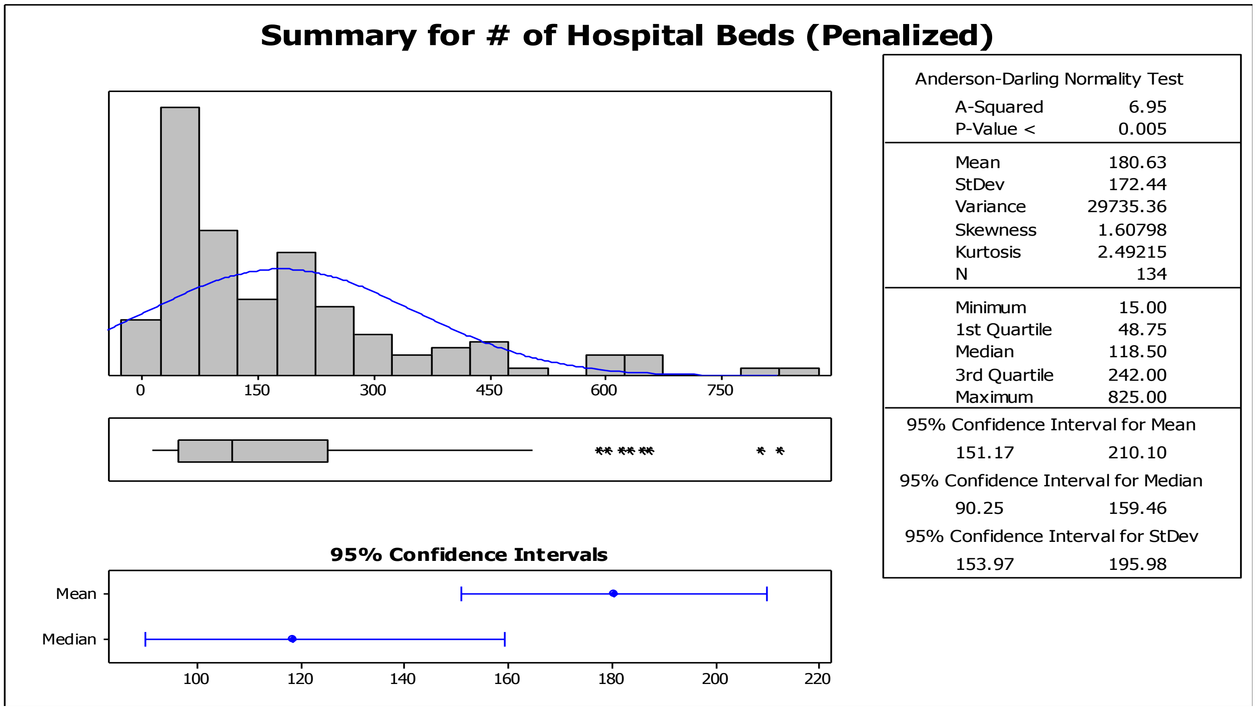


Figure 4.9 – Descriptive Statistics for Number of Hospital Beds

Mann-Whitney Test

H_0: Median (Beds) = Median (Penalty Status)

Number of Beds does not Impact Penalty Status (No Relationship)

H_1: Median (Beds) ≠ Median (Penalty Status)

Number of Beds does Impact Penalty Status (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

** TEST RESULTS **

	N	Median
BCAT_P_ORDINAL	134	2.5000
BCAT_NP_ORDINAL	98	1.5000

Point estimate for ETA1-ETA2 is -0.0000

95.0 Percent CI for ETA1-ETA2 is (-0.0002,0.9999)

W = 17130.0

Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0026

The test is significant at 0.0018 (adjusted for ties)

Conclusion: ($p = 0.0018$, $p < 0.05$), there is evidence that an association exists between Penalty Status and Number of Beds. In other words, Number of Beds predictor does Impact Penalty Status - a relationship exists.

4.3.2. Number of Admissions Analysis - Continuous Data

As indicated by Figure 4.10, the number of hospital admissions distribution is not normal, with an Anderson-Darling Normality test yielding a P-value < 0.05. The penalties were distributed across all hospitals, but it is evident that hospitals with admissions up to 2000 (the tallest bar) experienced the most penalties. There is a steady decline of penalty quantities as the number of admissions increased. The average number of admissions is about 8192.

Mann-Whitney Test

H_0: Median (Admission) = Median (Penalty Status)

Admissions do not Impact Penalty Status (No Relationship)

H_1: Median (Admission) ≠ Median (Penalty Status)

Admissions do Impact Penalty Status (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

** TEST RESULTS **

	N	Median
ACAT_P_ORDINAL	134	2.5000
ACAT_NP_ORDINAL	97	2.0000

Point estimate for ETA1-ETA2 is -0.0000

95.0 Percent CI for ETA1-ETA2 is (-0.0000,0.9999)

W = 17145.5

Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0014

The test is significant at 0.0009 (adjusted for ties)

Conclusion: ($p = 0.0009$, $p < 0.05$), there is evidence that an association exists between Penalty Status and Admission Number. In other words, Number of Admission does Impact Penalty Status - a relationship exists.

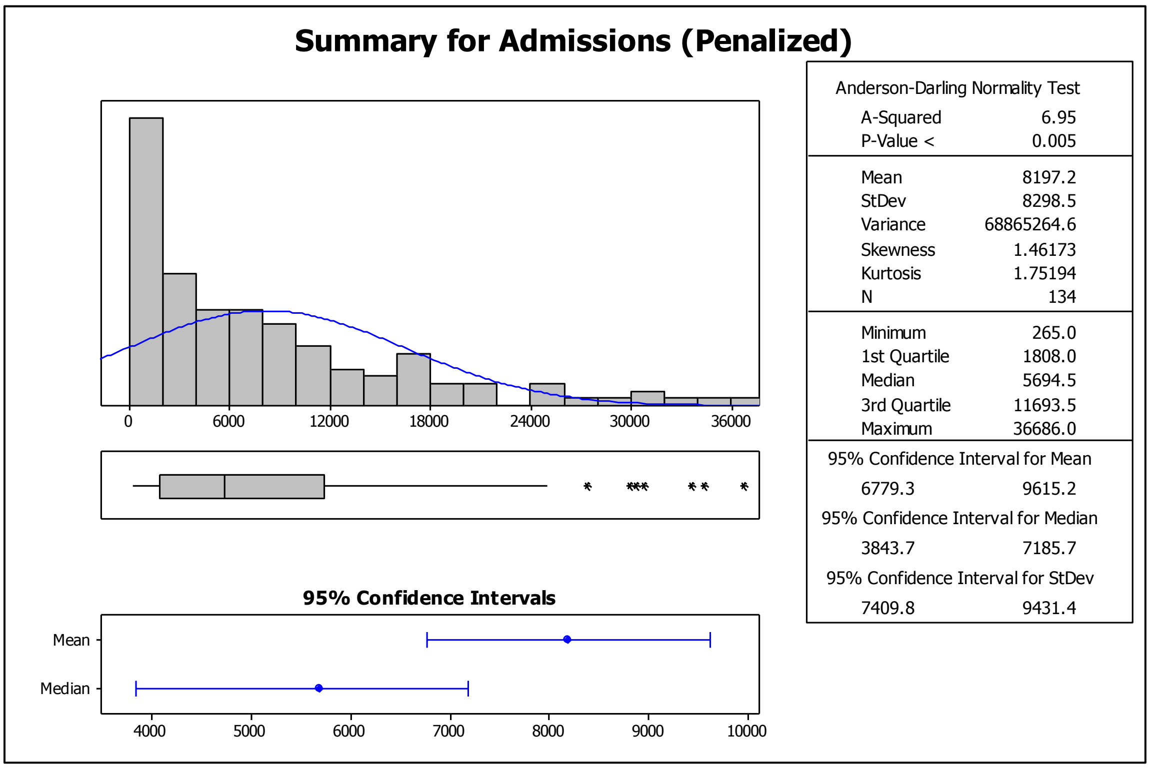


Figure 4.10: Descriptive Statistics for Hospital Admissions in Penalized Hospitals

4.3.3. Number of Personnel Analysis - Continuous Data

The number of hospital personnel working at the hospital can surely have an effect on the overall operation of a hospital. The ability of the staff to respond in a a timely fashion to the needs of the patient is very critical for success. The data is inclusive of all hospital staff (indirect or direct contact with patient), and Figure 4.11 below shows the dataset for hospital personnel is not normal – with an Anderson-Darling P-Value < 0.05. The average number of personnel for the penalized hospital was approximately 850.

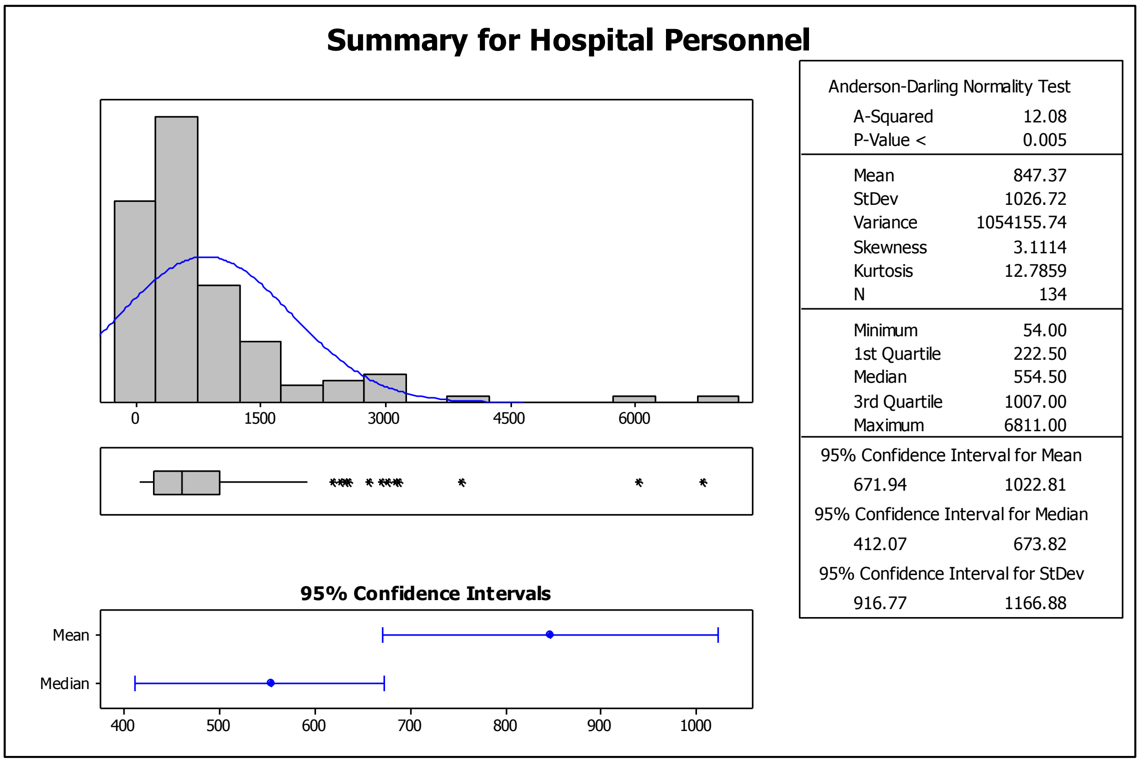


Figure 4.11: Descriptive Statistics for Hospital Personnel in Penalized Hospitals

Mann-Whitney Test

H_0: Median (Admission) = Median (Penalty Status)

Personnel do not Impact Penalty Status (No Relationship)

H_1: Median (Admission) ≠ Median (Penalty Status)

Personnel do Impact Penalty Status (Relationship Exists)

Rejection Criteria: At the 0.05 significance level, reject H_0 if $p < 0.05$

At the 0.05 significance level, fail to reject H_0 if $p > 0.05$

** TEST RESULTS **

	N	Median
PCAT_P_ORDINAL	134	2.5000
PCAT_NP_ORDINAL	98	2.0000

Point estimate for ETA1-ETA2 is 0.0000

95.0 Percent CI for ETA1-ETA2 is (0.0002,1.0000)

W = 16960.0

Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0076

The test is significant at 0.0056 (adjusted for ties)

Conclusion: ($p = 0.0056$, $p < 0.05$), there is evidence that an association exists between Penalty Status and Personnel. In other words, Number of Personnel does Impact Penalty Status - a relationship exists.

4.3.4. Non-Parametric Test Summary for Continuous Input Predictors

The descriptive statistics for all continuous predictors from the Input process step showed that the datasets were not normal, so the use of a non-parametric statistical tool, specially the Mann-Whitney technique was used to test the significance of Admissions, Personnel and Number of Beds to see if they will contribute to the predictor model.

The Mann-Whitney analyses showed that there is statistical evidence that the continuous Input predictors will have an impact on the determination of penalties, i.e. these predictors will not contribute to the model for predicting a hospital being penalized.

4.3.5. Correlation Analysis of Continuous Data for Input Variables

For brevity, the factors have been abbreviated in the analysis:

PEN = Penalty %,

B = number of beds,

A = admissions,

P = number of personnel

The correlation matrix output for these factors is shown in Figure 5.12, and the diagonal plots and plots above them will be ignored, for the upper is simply a reflection of the bottom plots.

In reviewing the plots, it is evident that the correlation amongst the plots varies. There are strong correlations between, admissions vs. bed, admissions vs. personnel, and personnel vs. bed. From a logical standpoint, it is expected that these correlations will exist. The number of patients admitted to the hospital will be dependent on the number of beds inside the hospital and the hospital should staff the hospital based on the number of beds there. All three correlations are relatively strong and positive in nature; however, there slope for the plot for admissions vs. beds is much steeper, when compared to the other two plots.

There is no apparent correlation between any factor and penalties, but further analysis is required to prove or disprove this observation.

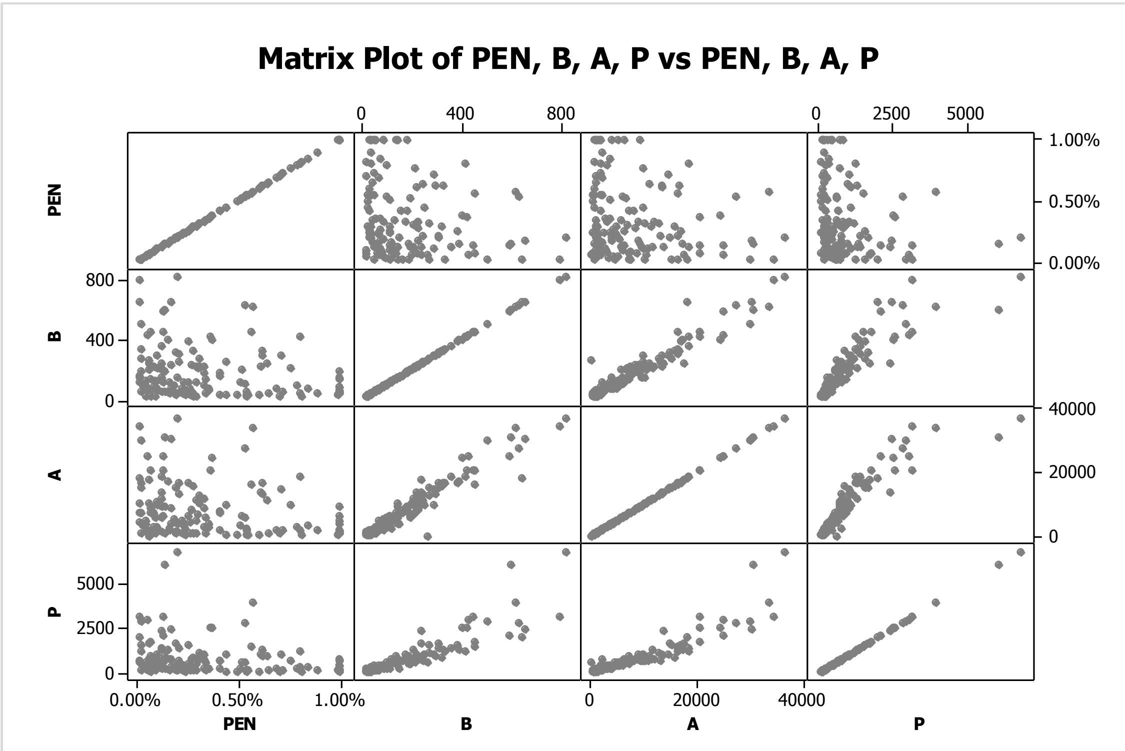


Figure 4.12: Correlation Matrix of Continuous Input Predictors

Correlations: PEN, B, A, P

	PEN	B	A
B	-0.217		
	0.012		
A	-0.213	0.960	
	0.014	0.000	
P	-0.209	0.881	0.904
	0.015	0.000	0.000

The correlations analysis above supports and confirms the graphical summary that is shown in Figure 4.12. The Pearson correlation between Admissions and Number of Beds is 0.960, between Admissions and Personnel is 0.904, and between Personnel and Number of Beds is 0.881.

The large positive correlation value suggests that as one predictor increases in value, the other increases in value as well. The small negative pearson coeffients that are shown for the correlations between penalties and the three predictor values suggests an inverse relationship that is not too strong.

The corresponding p-values are all less the 0.05, and in some instances, less than a 0.01 significance level, thus indicating that the correlations are significant. These results are consistent with the Manns-Whitney test results of significance and confirms that the individual analyses suggests that they will contribute to the model.

It should be noted that multicollinearity could be an issue due to the high correlations between number of beds, admissions and personnel. The presence of multicollinearity will increase standard errors and could thus lead to their elimination from the model, when in fact they should be included as viable predictors. At this level, it is expected that a regression with all variables in the model could possibly result in some being eliminated.

The following regression results were run to check for multicollinearity, and it was confirmed that it is an issue, considering the Variance Inflation Factors (VIF) were all greater than 7.

VIF Results – Check #1

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.0040660	0.0003700	10.99	0.000	
B	-0.00000251	0.00000530	-0.47	0.637	13.015
A	0.00000000	0.00000012	0.01	0.993	16.004
P	-0.00000024	0.00000058	-0.41	0.679	5.544

Observation of Check #1 Regression: the presence of B (number of beds) and A (Admissions) resulted in VIF values > 7 for both. Previous analysis (re-copied below for convenience) showed that the Pearson coeffient between B and A is equal to 0.960, which happens to be the highest coeffient, implying that the two predictor variables are highly correlated. It should also be noted that the presence of multicollinearity will result in the absence of significant predictors, which is seen in the above results - all p-values are greater than 0.05.

Correlations: PEN, B, A, P

	PEN	B	A
B	-0.217		
	0.012		
A	-0.213	0.960	
	0.014	0.000	
P	-0.209	0.881	0.904
	0.015	0.000	0.000

VIF Results – Check #2

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.0040866	0.0003655	11.18	0.000	
B	-0.00000274	0.00000525	-0.52	0.603	12.874
A	-0.00000002	0.00000011	-0.19	0.846	12.874

Observation of Check #2 Regression: the presence of B (number of beds) and A (Admissions) resulted in VIF values > 7 for both. All p-values are greater than 0.05, so naturally, no predictors are significant.

VIF Results – Check #3

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.0040212	0.0003566	11.27	0.000	
A	-0.00000005	0.00000007	-0.64	0.522	5.484

P	-0.00000027	0.00000058	-0.47	0.641	5.484

Observation of Check #3 Regression: the presence of A (admissions) and P (personnel) actually resulted in a VIF value less than 7. Multicollinearity will not be an influence in a model with these two predictors in them.

VIF Results – Check #4

Predictor	Coef	SE Coef	T	P	VIF
Constant	0.0040660	0.0003685	11.03	0.000	
B	-0.00000247	0.00000309	-0.80	0.426	4.460
P	-0.00000024	0.00000052	-0.46	0.647	4.460

Observation of Check #4 Regression: the presence B (number of beds) and P (personnel) has reduced the VIF value even more, and since the number is less than 7, multicollinearity will not be an issue for a model with both of these variables.

To address multicollinearity for these highly correlated variables, Admissions will be a prime candidate for removal from the model. In the four observation summaries from the Checks above, it is noted that the presence of A (admissions) resulted in the high VIF's. Furthermore, it was linked to the highest Pearon correlation coefficient.

4.4 Model Formation of Input Process Parameters – SUBGROUPED DATA

The secondary analysis of the Input Process parameters is intended to get an understanding of how the data analyses will change if the data is compiled into logical subgroups or segmentations. The intent in running this analysis is to determine the ideal way to represent data in the final model, which will be essential for the interpretation of the results of the vital factors the model is comprised of. Naturally, this segmentation of raw data is not inclusive of the categorical data, which by virtue of the data itself, is already categorized.

The segmentation of the continuous data into subgroups will be done based on the quartiles of each dataset: the 1st quartile, 2nd quartile (median) and the 3rd quartile. Table 4.5 shows the data intervals for the three continuous datasets: number of beds, admissions and personnel. These intervals will be used to divide up the data the subsequent analyses will be based on these groups.

Table 4.5: Categorization of Continuous Input Predictors

Beds (New Variable)	Admissions (New Variable)	Personnel (New Variable)
Less than 50 **(B1)**	Less than 1810 **(A1)**	Less than 225 **(P1)**
51 ≤ Beds ≤ 120 **(B2)**	1811 ≤ Admissions ≤ 5695 **(A2)**	226 ≤ Beds ≤ 555 **(P2)**
121 ≤ Beds ≤ 250 **(B3)**	5696 ≤ Admissions ≤ 11694 **(A3)**	555 ≤ Beds ≤ 1010 **(P3)**
Greater than 250 **(B4)**	Greater than 11694 **(A4)**	Greater than 1010 **(P4)**

Moving forward, this continuous data will now be referenced by the categorical subgroupings as noted above, and the analysis done on this data will be conducted using techniques for categorical data, not continuous data. A comparison of the models generated from both types will be done, and format that renders the best model will be used after that point.

4.4.1. Model Construction of Categorized (Sub-grouped) Input Variables

The establishment of a model for predicting the receipt of penalties with the Input parameters is of some technical merit. As was mentioned before, these parameters are innate to the hospital itself, and they do not change very regularly. The continuous dataset will not be constant, but will experience some marginal change over time, or even on a constant basis. The factor driven data will be less likely to change, but it certainly can over time. The question now is, whether or not certain hospitals are innately destined to receive penalties? The analysis of the Input data alone, will answer that question.

* * * MODEL 1 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: O, BCAT, ACAT, E, T, PCAT

Factor Information – Full Model

Factor	Levels	Values
O	3	Government, Non-Profit, Proprietary
BCAT	4	B1, B2, B3, B4
ACAT	4	A1, A2, A3, A4
E	2	rural, urban
T	2	non-teaching, teaching
PCAT	4	P1, P2, P3, P4

Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	0.484703	0.387031	1.25	0.210			
O							
Non-Profit	-0.0703393	0.450984	-0.16	0.876	0.93	0.39	2.26
Proprietary	-0.779713	0.484635	-1.61	0.108	0.46	0.18	1.19
BCAT							
B2	0.929272	0.614895	1.51	0.131	2.53	0.76	8.45
B3	0.727133	0.963566	0.75	0.450	2.07	0.31	13.68
B4	1.33459	1.21629	1.10	0.273	3.80	0.35	41.20
ACAT							
A2	0.463443	0.615500	0.75	0.451	1.59	0.48	5.31
A3	2.72975	1.06622	2.56	0.010	15.33	1.90	123.90
A4	2.69569	1.29668	2.08	0.038	14.82	1.17	188.13
E							
urban	-1.12475	0.432501	-2.60	0.009	0.32	0.14	0.76
T							
teaching	-0.928795	0.449814	-2.06	0.039	0.40	0.16	0.95
PCAT							
P2	-0.0034406	0.559359	-0.01	0.995	1.00	0.33	2.98
P3	-0.670675	0.942696	-0.71	0.477	0.51	0.08	3.24
P4	-2.06393	1.28029	-1.61	0.107	0.13	0.01	1.56

Log-Likelihood = -132.843

Test that all slopes are zero: G = 48.597, DF = 13, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P

Pearson	80.9452	59	0.031
Deviance	97.5916	59	0.001
Hosmer-Lemeshow Brown:	19.0799	8	0.014
General Alternative	11.6496	2	0.003
Symmetric Alternative	1.1968	1	0.274

* * * MODEL 1 END * * *

At the 95% confidence / 0.05 significance level, it is noted that there are some critical factors or significant predictors to consider from Model 1, and hence, the existence of a model to predict the receipt of penalties. These critical predictors have a P-value < 0.05.

Significant at 95% Confidence level: ACAT (A3, A4), Urban, Teaching

The Goodness of Fit results yielded P-values < 0.05 level of significance, so the conclusion must be made that the model does not adequately describe the data – the model is not an acceptable one as is.

Model 1 represents the Full-Model for the INPUT Process step; however, as was noted above, not all factors are significant. A secondary and partial model with the significant factors will be run to determine new and more accurate parameter estimates. This reduced model is represented by Model 2, and the analysis follows.

*   *   * MODEL 2 BEGIN *   *   *

Method: Binary Logistic Regression

Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)

Model Inputs: ACAT, E, T

Factor Information – Reduced Model

Factor	Levels	Values
ACAT	4	A1, A2, A3, A4
E	2	rural, urban
T	2	non-teaching, teaching

Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	0.384945	0.298303	1.29	0.197			
ACAT							
A2	0.970768	0.385830	2.52	0.012	2.64	1.24	5.62
A3	2.52133	0.503247	5.01	0.000	12.45	4.64	33.37
A4	2.10802	0.506499	4.16	0.000	8.23	3.05	22.21
E							
urban	-1.42441	0.371383	-3.84	0.000	0.24	0.12	0.50
T							
teaching	-0.896974	0.436562	-2.05	0.040	0.41	0.17	0.96

Log-Likelihood = -136.702

Test that all slopes are zero: G = 40.877, DF = 5, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	6.41676	8	0.601
Deviance	7.57967	8	0.476
Hosmer-Lemeshow Brown:	3.18755	6	0.785
General Alternative	1.78816	2	0.409
Symmetric Alternative	0.46824	1	0.494

* * * MODEL 2 END * * *

At the 95% confidence / 0.05 significance level, it is noted that all of the predictors in this reduced model are significant and must be included in the model to predict the receipt of penalties. These critical predictors have a P-value < 0.05 (bold).

The Goodness of Fit results yielded P-values > 0.05 level of significance, so the conclusion must be made that the model does adequately describe the data – the model is an acceptable one, and Table 4.6 summarizes the estimated model parameters for the INPUT process step. This model is a predictor model for the INPUT factors that are innate to the hospital to determine whether or not the hospital will be penalized.

Table 4.6: Model for INPUT Process Step (95% Confidence)

Model Variable	Variable Description	Estimated Coefficients
Constant	Constant Term	0.384945
A2	Hospital Admissions [1811 – 5695]	0.970768
A3	Hospital Admissions [5696 – 11694]	2.52133
A4	Hospital Admissions > 11694	2.10802
E (Urban)	Hospitals in Urban Environments	-1.42441
T (Teaching)	Hospitals Utilized for Teaching/Instruction	-0.896974

If the prime goal was to construct a model using the INPUT data only, it would be perfectly acceptable to stop at this point and take a closer look at the output data analysis. An evaluation of the odds ratios for the predictors in the reduced model reveals key information. The fitted model gives the following interpretations for each variable, assuming that all others are held constant:

- The odds of an A2 hospital being penalized over the odds of an A1 hospital being penalized are 2.64. In terms of percent change, the odds for receiving Medicare penalties for an A2 hospital are 164% higher than the odds for an A1 hospital.

- The odds of an A3 hospital being penalized over the odds of an A1 hospital being penalized are 12.45. In terms of percent change, the odds for receiving Medicare penalties for an A3 hospital are 1145% higher than the odds for an A1 hospital.

- The odds of an A4 hospital being penalized over the odds of an A1 hospital being penalized are 8.23. In terms of percent change, the odds for receiving Medicare penalties for an A3 hospital are 723% higher than the odds for an A1 hospital.

- The odds of an urban hospital being penalized over the odds of a rural hospital being penalized are 0.24. In terms of percent change, the odds for receiving Medicare penalties for an urban hospital are 24% higher than the odds for a rural hospital.

- The odds of a teaching hospital being penalized over the odds of a non-teaching hospital being penalized are 0.41. In terms of percent change, the odds for receiving Medicare penalties for a teaching hospital are 41% higher than the odds for a non-teaching hospital.

4.5 Model Formation of Input Process Parameters – UNGROUPED DATA

The INPUT process will now be evaluated with the raw data. In the previous section, the continuous data were categorized and segmented to facilitate the model formation; however, the following analysis (Model 3) will be performed without grouping. A comparison of both models (grouped/not grouped data) will be done.

* * * MODEL 3 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: O, B, A, E, T, P

Factor Information – Full Model

Factor	Levels	Values
O	3	Government, Non-Profit, Proprietary
E	2	rural, urban
T	2	non-teaching, teaching

Logistic Regression Table

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	0.837235	0.355366	2.36	0.018			
O							
Non-Profit	0.0826808	0.417284	0.20	0.843	1.09	0.48	2.46
Proprietary	-0.502544	0.438355	-1.15	0.252	0.60	0.26	1.43
B	0.0002361	0.0031092	0.08	0.939	1.00	0.99	1.01
A	0.0000401	0.0000706	0.57	0.570	1.00	1.00	1.00
E							
urban	-0.507419	0.364732	-1.39	0.164	0.60	0.29	1.23
T							
teaching	-0.588165	0.419356	-1.40	0.161	0.56	0.24	1.26
P	-0.0002379	0.0003454	-0.69	0.491	1.00	1.00	1.00

Log-Likelihood = -151.532

Test that all slopes are zero: G = 11.218, DF = 7, P-Value = 0.129

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	232.469	223	0.318
Deviance	303.064	223	0.000
Hosmer-Lemeshow Brown:	36.279	8	0.000
General Alternative	10.339	2	0.006
Symmetric Alternative	9.511	1	0.002

* * * MODEL 3 END * * *

At the 95% confidence / 0.05 significance level, it is noted that Model 3 has no critical factors or significant predictors to consider since all the P values > 0.05.

The Goodness of Fit results yielded P-values < 0.05 level of significance, with the exception of Pearson - this suggests that the model is not a good fit.

A review of the odds ratios for all six, show that all variables except Propriety, Urban and Teaching have a ratio = 1. An odds ratio equally 1 implies that the receipt of Medicare penalties is independent of those particular variables; however, the three noted predictors have odds ratios equaling: 0.6, 0.6, and 0.56 respectively. It would be tempting to conclude that they are significant to predicting penalties, but a closer review of their corresponding confidence intervals clearly indicates that 1 is included, so the conclusion could be made that no variables (in this form) contributes to a model that can adequately describe the data. The issue of multicollinearity is revisited, and it is not surprising that there are no significant predictors. Based on the previous discussion, the variable Admissions will be removed to see the resulting effect on the model. At the 0.05 significance level, there are no predictor variables that contribute to the model. The model with only the raw, uncategorized continuous data is not the best choice.

4.6 Preferred Model form for Input Process Parameters

A comparison of both grouped and ungrouped Input data was done and the respective analyses were performed. It is evident that the preferred format for representing the Input data is put place the continuous data in segmented or grouped form. The grouping of the continuous data into subgroups yielded a more favorable response in terms of one's ability to construct an acceptable model for predictive purposes, so it will be concluded that the estimated parameters for the Input process step, at a 95% confidence, is represented by Table 4.6.

4.7 Model Formation of Operational Process Parameters

The Operations Process step accounts for six top level key elements that are typically tracked within the regular operation of the hospital; namely, Registry affiliation, Communications, Quality of Service, Time (Quality), Medicare Volume and Payment. The availability of this data enables the analyses and allows the top level elements to be further sub-divided, as shown below in Tables 4.7 and Table 4.8.

Table 4.7: Operations Process Step Variables Chart (Part 1)

VARIABLE	DETAILED DATA DESCRIPTION	TOP LEVEL DESCRIPTION	DATA TYPE
PI	Spending per Hospital Patient with Medicare	Payment Index	Continuous
V	Medicare Volume	Number of Cases	Continuous
NC1	Percent of patients who reported that their nurses "Sometimes" or "Never" communicated well.	Nurse Communication	Continuous
NC2	Percent of patients who reported that their nurses "Usually" communicated well.	Nurse Communication	Continuous
NC3	Percent of patients who reported that their nurses "Always" communicated well.	Nurse Communication	Continuous
DC1	Percent of patients who reported that their doctors "Sometimes" or "Never" communicated well.	Doctor Communication	Continuous
DC2	Percent of patients who reported that their doctors "Usually" communicated well.	Doctor Communication	Continuous
DC3	Percent of patients who reported that their doctors "Always" communicated well.	Doctor Communication	Continuous
HT1	Percent of patients who reported that they "Sometimes" or "Never" received help as soon as they wanted.	Help Time	Continuous
HT2	Percent of patients who reported that they "Usually" received help as soon as they wanted.	Help Time	Continuous
HT3	Percent of patients who reported that they "Always" received help as soon as they wanted.	Help Time	Continuous
PM1	Percent of patients who reported that their pain was "Sometimes" or "Never" well controlled.	Pain Management	Continuous
PM2	Percent of patients who reported that their pain was "Usually" well controlled.	Pain Management	Continuous
PM3	Percent of patients who reported that their pain was "Always" well controlled.	Pain Management	Continuous

Table 4.8: Operations Process Step Variables Chart, Part 2

VARIABLE	DETAILED DATA DESCRIPTION	TOP LEVEL DESCRIPTION	DATA TYPE
CQ1	Percent of patients who reported that their room and bathroom were "Sometimes" or "Never" clean.	Cleanliness Quality	Continuous
CQ2	Percent of patients who reported that their room and bathroom were "Usually" clean.	Cleanliness Quality	Continuous
CQ3	Percent of patients who reported that their room and bathroom were "Always" clean.	Cleanliness Quality	Continuous
SQ1	Percent of patients who reported that the area around their room was "Sometimes" or "Never" quiet at night.	Solitude Quality	Continuous
SQ2	Percent of patients who reported that the area around their room was "Usually" quiet at night.	Solitude Quality	Continuous
SQ3	Percent of patients who reported that the area around their room was "Always" quiet at night.	Solitude Quality	Continuous
OQ1	Percent of patients who gave their hospital a rating of 6 or lower on a scale from 0 (lowest) to 10 (highest).	Overall Quality	Continuous
OQ2	Percent of patients who gave their hospital a rating of 7 or 8 on a scale from 0 (lowest) to 10 (highest).	Overall Quality	Continuous
OQ3	Percent of patients who gave their hospital a rating of 9 or 10 on a scale from 0 (lowest) to 10 (highest).	Overall Quality	Continuous
RQ1	Percent of patients who reported NO,they would not recommend the hospital.	Quality-Recommendation	Continuous
RQ2	Percent of patients who reported YES,they would probably recommend the hospital.	Quality-Recommendation	Continuous
RQ3	Percent of patients who reported YES,they would definitely recommend the hospital.	Quality-Recommendation	Continuous
R1	Cardiac Surgery Registry	Structural Measure	Categorical
R2	Stroke Care Registry	Structural Measure	Categorical
R3	Nursing Care Registry	Structural Measure	Categorical
R4	e-Lab	Able to receive labs electronically	Categorical
R5	Track	Able to track patients lab results, tests, and	Categorical

The logistic model was run without data segmentation or regrouping. To eliminate col-linearity issues, only the worst case scenarios (lowest rankings) were included in the model, i.e.

NC1, DC1, HT1, PM1, CQ1, SQ1, OQ1 and RQ1. Model 4 shows the results of the logistic regression for the Operations dataset.

* * * MODEL 4 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: PI V NC1 DC1 HT1 PM1 CQ1 SQ1 OQ1 RQ1 R1 R2 R3 R4 R5

Logistic Regression Table (Full Model)

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-0.837477	1.74649	-0.48	0.632			
PI	-0.0061240	1.73126	-0.00	0.997	0.99	0.03	29.58
V	-0.0001296	0.00027	-0.47	0.637	1.00	1.00	1.00
NC1	-19.6696	17.2939	-1.14	0.255	0.00	0.00	1.5E6
DC1	-23.6979	11.5069	-2.06	<u>0.039</u>	0.00	0.00	0.32
HT1	9.32715	7.25786	1.29	0.199	1.1E4	0.01	1.6E10
PM1	-22.8659	9.98687	-2.29	<u>0.022</u>	0.00	0.00	0.04
CQ1	2.42772	5.89601	0.41	0.681	11.33	0.00	1.18E6
SQ1	16.7505	6.68566	2.51	<u>0.012</u>	1.8E7	38.35	9.2E+12
OQ1	25.7622	10.7113	2.41	<u>0.016</u>	1.5E11	117.73	2 2.0E20
RQ1	2.01668	13.2491	0.15	0.879	7.51	0.00	1.4E12
R1							
yes	0.327858	0.49974	0.66	0.512	1.39	0.52	3.70
R2							
yes	0.105141	0.44271	0.24	0.812	1.11	0.47	2.65
R3							
yes	-0.680534	0.3985	-1.71	0.088	0.51	0.23	1.11
R4							

yes	1.00991	0.747806	1.35	0.177	2.75	0.63	11.89
R5							
yes	-0.477302	0.722926	-0.66	0.509	0.62	0.15	2.56

Log-Likelihood = -135.337

Test that all slopes are zero: G = 44.236, DF = 15, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	229.553	215	0.236
Deviance	270.675	215	0.006
Hosmer-Lemeshow	15.637	8	0.048

* * * MODEL 4 END * * *

At the 95% confidence / 0.05 significance level, in Model 4 it is noted that there 4 significant predictors to consider since their P values > 0.05. The predictors that will contribute to the model are in bold text.

The Pearson Goodness of Fit test yielded a P-value > 0.05 level of significance, which suggests that the model is a good fit. Model 5 below represents a Reduced Model with only these four significant factors. All independent variables are significant, thus providing the Operations variables that will be used in the final model.

* * * MODEL 5 BEGIN * * *

Method: Binary Logistic Regression

Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)

Model Inputs: DC1 PM1 SQ1 OQ1

Logistic Regression Table (Reduced Model)

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-0.600259	0.450510	-1.33	0.183			
DC1	-23.4424	10.1186	-2.32	0.021	0.00	0.00	0.03
PM1	-21.2856	9.00865	-2.36	0.018	0.00	0.00	0.03
SQ1	16.6327	5.66963	2.93	0.003	1.6E7	2.5E2	1.1E12
OQ1	26.5333	8.14504	3.26	0.001	3.3E11	3.89E4	2.9E18

Log-Likelihood = -139.409

Test that all slopes are zero: G = 37.193, DF = 4, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	228.158	217	0.288
Deviance	261.136	217	0.022
Hosmer-Lemeshow	29.150	8	0.000

* * * MODEL 5 END * * *

Table 4.9 Model for Operation Process Step

Model Variable	**Variable Description**	**Estimated Coefficients**
Constant	Constant Term	-0. 600259
DC1	Doctors "Sometimes" or "Never" communicated well	-23.4424
PM1	Pain was "Sometimes" or "Never" well controlled	-21.2856
SQ1	Area near room "Sometimes" or "Never" quiet at night	16.6327
OQ1	Overall Hospital Quality rating of 6 or lower	26.5333

4.8 Model Formation of Output Process Parameters

The Output process predictors are focused on elements related to the discharge process, or the transitional steps that facilitates the release of a patient from the hospital. These are by far the most critical actions to prevent a patient from being readmitted.

The data compiled for analysis is listed below. These activities are done before the patient is released, or even during the stay in the hospital. These are the last actions that are done to ensure the patient is prepared to be released from the hospital, and if certain things are not clear, the patient may do something wrong that could result in them being readmitted within 30 days.

All predictors cannot be included in the model due to collinearity. The Pearson coefficient analysis below indicates this.

Table 4.10: Output Process Step Variables Chart

VARIABLE	DETAILED DATA DESCRIPTION	TOP LEVEL DESCRIPTION	DATA TYPE
DI1	Percent of patients who reported that YES,they were given information about what to do during their recovery at home.	Discharge Instructions	Continuous
DI2	Percent of patients who reported that they were not given information about what to do during their recovery at home.	Discharge Instructions	Continuous
DM1	Percent of patients who reported that staff "Sometimes" or "Never" explained about medicines before giving it to them.	Discharge-Medicine	Continuous
DM2	Percent of patients who reported that staff "Usually" explained about medicines before giving it to them.	Discharge-Medicine	Continuous
DM3	Percent of patients who reported that staff "Always" explained about medicines before giving it to them.	Discharge-Medicine	Continuous

Correlations: DI1, DI2, DM1, DM2, DM3

	DI1	DI2	DM1	DM2
DI2	-1.000			
	*			
DM1	-0.529	0.529		
	0.000	0.000		
DM2	-0.145	0.145	0.303	
	0.027	0.027	0.000	
DM3	0.467	-0.467	-0.896	-0.694
	0.000	0.000	0.000	0.000

Cell Contents: Pearson correlation
P-Value

The coefficient matrix above indicates that all predictor relations are strong, the inclusion of all variables will lead to Multicollinearity – at least 2 of the variables will have to be removed, one from the D1 pair and one from the D2 set.

Similar to the regression for the operations step, the variable that yielded the worst outcome will be used, so the resulted in elimination of DI1 and DM3, this quite adequate also considering the goal is to predict penalties.

A series of logistic regressions were not done to determine the significant predictors and thus be included in the model.

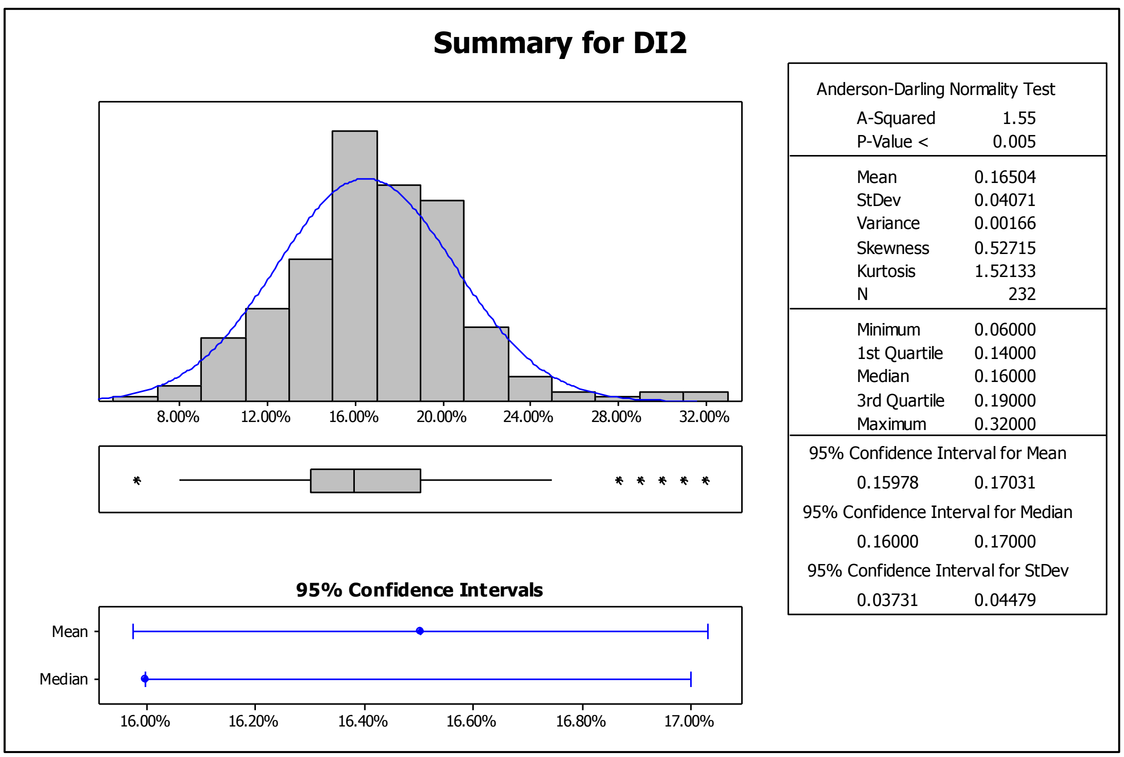


Figure 4.13: Graphical Summary of DI2 Discharge data.

4.8.1 Analysis of Continuous Predictors for the Output Process Step

The graphical summary for DI2 revealed that the distribution is not normal (see Figure 4.13). The central part of the plot has an appearance of normality, but the extreme ends are the issue, leading to non-normality.

There are outliers that have skewed the tail of the distribution rendering it non-normal, and the Anderson Darling test has a value less than 0.05, implying non-normalcy. There is great overlap with the mean and median. The mean is 0.16504, which implies that almost 17% of the patients did not feel the discharge information provided the medical staff was adequate. The median is 16%, and maximum and minimum values respectively are 6% and 32%.

If 16% as average, and up to 32% of the patients are saying that they don't have right information to recover at home, that could potentially lead to them doing something incorrect and thus return to the hospital, quite possibly before the 30 days pass.

Figure 4.14 highlights the graphical summary for DM1, which gives an indication of how well the medical staff communicated to the patient about the medicines they were taking. If the doctor orders medication, and a nurse gives the patient the medicine, most likely they will take it. Oftentimes, not much personal care is taken to go the extra mile to become personal.

The patient should be informed about how important the medicine is, and the role it plays in their recovery. If they don't know what it is, they may not value the medicine as much, and according to the graphical summary, almost 19% of the patients stated that they were not informed about the medicine they were taking, the actual score represents (Never or Sometimes told). "Sometimes" might as well be considered never, considering you are dealing with elderly patients who may have problems remembering. If they are told often enough, they just might remember.

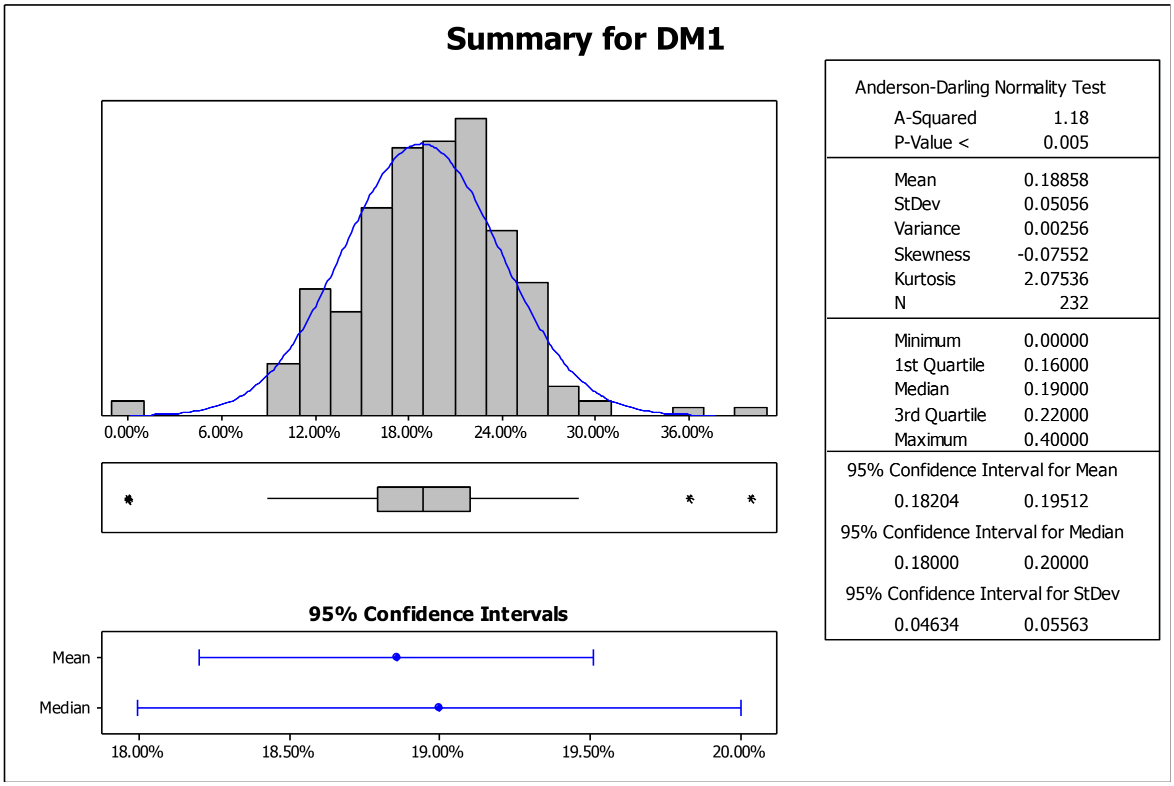


Figure 4.14: Graphical Summary for DM1 Discharge Data

The Anderson Darling test statistic is < 0.05, thus indicating that the data is not normal. data is not normal, and the maximum value is 40% - that is almost have of the patients stating they really don't know the medications they are on - that will lead to issues.

Patients who were usually told about the medicine they were given are captured in the DM2 dataset. The Anderson Darling test statistic is = 0.005, which is less than 0.05, thus indicating that the data is not normal, as shown in Figure 4.15. The ends of the distribution are suspect for this result, considering the amount of outliers indicated in the graphic. The average amount of patients stating they were usually told about their medication before taking it was about 17%, with the maximum and minimum being 3% and 2% respectively.

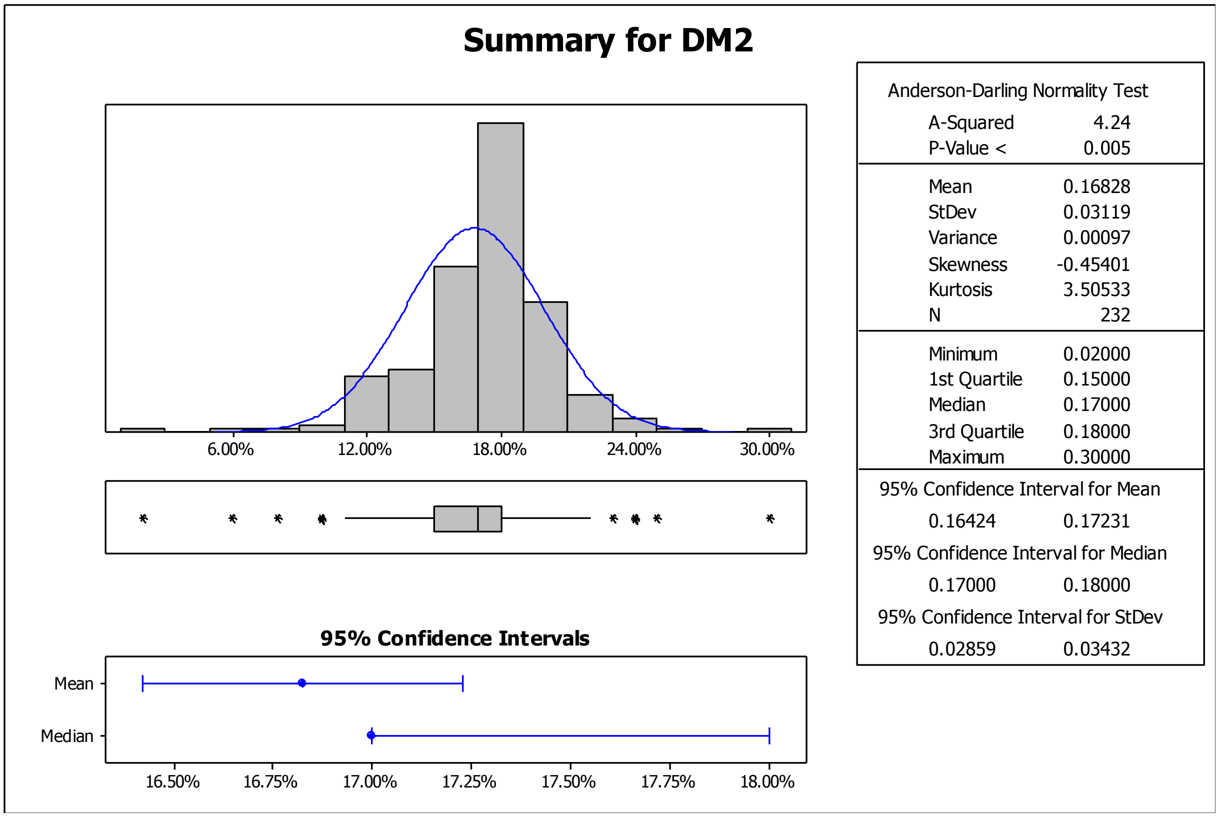


Figure 4.15: Graphical Summary for DM2 Discharge Data

4.8.2 Model Construction of Predictors in the Output Process Step

The predictors have been narrowed done to three: DI2, DM1, DM2 and the goal is to establish a sub-model for this last process step.

* * * MODEL 6 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: DI1 DM1 DM2

Logistic Regression Table (Full Model)

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-1.00722	0.879722	-1.14	0.252			
DI2	7.30296	4.07408	1.79	0.073	1.5E3	0.51	4360117.00
DM1	3.17162	3.33220	0.95	0.341	23.85	0.03	16360.37
DM2	-2.79322	4.58392	-0.61	0.542	0.06	0.00	488.38

Log-Likelihood = -154.003
Test that all slopes are zero: G = 8.005, DF = 3, P-Value = 0.046
Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	203.358	206	0.539
Deviance	267.098	206	0.003
Hosmer-Lemeshow	6.493	8	0.592

Table of Observed and Expected Frequencies:

* * * MODEL 6 END * * *

A Full Model represented by Model 6, with the Output predictors yielded no significant variables. The Pearson Goodness of Fit statistic was high, and the P-value is less than 0.05, implying the model was a good fit. This is unusual considering no predictors were significant - three separate regressions of the variables did render significant factors at the 0.05 significance level. The confidence intervals for all three variables include 1, hence the no significance status.

* * * MODEL 7 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: DI2 DM1

Logistic Regression Table (Partial)

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-1.37338	0.647540	-2.12	0.03			
DI2	7.30824	4.06087	1.80	0.072	1492.55	0.52	4.2E6
DM1	2.60889	3.18810	0.82	0.413	13.58	0.03	7026.57

Log-Likelihood = -154.189
Test that all slopes are zero: G = 7.633, DF = 2, P-Value = 0.022

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	145.400	138	0.316
Deviance	189.644	138	0.002
Hosmer-Lemeshow	7.443	8	0.490

* * * MODEL 7 END * * *

Model 7 uses only 2 variables (DI2 and DM1); however, it is not a good model to consider either, for there are no significant predictors to add to the overall model - all the P-Values are greater than 0.05.

* * * MODEL 8 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: DI2 DM2

Logistic Regression Table (Partial)

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-0.923978	0.873899	-1.06	0.290			
DI2	9.20063	3.57973	2.57	<u>0.010</u>	9.9E3	8.89	1.1E7
DM2	-1.60190	4.40659	-0.36	0.716	0.20	0.00	1135.55

Log-Likelihood = -154.458
Test that all slopes are zero: G = 7.095, DF = 2, P-Value = 0.029

* * * MODEL 8 END * * *

Similarly, Model 8 uses only 2 variables (DI2 and DM2); however, in this case, the DI2 is deemed a significant predictor with a P-Value = 0.01. We have one variable to add to the overall model - the P-Values is greater than 0.05.

* * * MODEL 9 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: DM1 DM2

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	-0.359418	0.793049	-0.45	0.650			
DM1	6.14406	2.90585	2.11	<u>0.034</u>	465.94	1.57	1.39E5
DM2	-2.84944	4.53693	-0.63	0.530	0.06	0.00	421.06

Log-Likelihood = -155.664
Test that all slopes are zero: G = 4.684, DF = 2, P-Value = 0.096

* * * MODEL 9 END * * *

Model 9 uses 2 variables (DM1 and DM2) as well; and DM1 is deemed a significant predictor with a P-Value = 0.034. The lower confidence value is very close to 1, and this explains the Chi Square overall P-Value of 0.096 – it is too close to not be significant.

4.8.3 Non-Parametric Test on Output data

The non-parametric tests below serve to determine if the individual predictors are significant when the response variable is factored in. The statement of significance at the end of each analysis sums up the test results.

Mann-Whitney Test and CI: Penalized, DM1

	N	Median
Penalized	232	1.0000
DM1	232	0.1900

Point estimate for ETA1-ETA2 is 0.7600

95.0 Percent CI for ETA1-ETA2 is (0.7400,0.7799)

W = 58214.0

Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0031

The test is significant at 0.0026 (adjusted for ties)

Mann-Whitney Test and CI: Penalized, DI2

	N	Median
Penalized	232	1.0000
DI2	232	0.1600

Point estimate for ETA1-ETA2 is 0.8000

95.0 Percent CI for ETA1-ETA2 is (0.7700,0.8100)

W = 58116.0

Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0038

The test is significant at 0.0033 (adjusted for ties)

Mann-Whitney Test and CI: Penalized, DM2

	N	Median
Penalized	232	1.0000
DM2	232	0.1700

Point estimate for ETA1-ETA2 is 0.8100
95.0 Percent CI for ETA1-ETA2 is (0.7900,0.8100)
W = 58116.0
Test of ETA1 = ETA2 vs ETA1 not = ETA2 is significant at 0.0038
The test is significant at 0.0032 (adjusted for ties)

The Man-Whitney tests above indicate that all three predictor values will contribute to the predictor model for penalties. This information must be balanced with the previous regressions analyses. In all regressions, DM2 was never determined to be a significant contributor, so it will be removed and not be considered for the final model, and Model 10 confirms this decision. It is the regression of DM2 on Penalty (the response) and it is clearly not a contributor, with the P-Value being greater than 0.05.

4.9 Final Model Formulation - Inclusive of all Significant Predictors

4.9.1 Collection of all Significant Predictors

Model 10 represents a combination of all the significant predictors determined from the previous Models from the 3 process steps. Recall that significant predictors from the various steps:

- Input Step: Admissions (ACAT), Environment (E), Teaching Status (T)
- Operations Step: DC1, PM1, SQ1, OQ1
- Output Step: DI2, DM1

4.9.2 Model Construction of all Significant Predictors

* * * MODEL 10 BEGIN * * *

Method: Binary Logistic Regression

Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)

Model Inputs: ACAT E T DC1 PM1 SQ1 OQ1 DM1 DM2

Logistic Regression Table – Full Model

					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Constant	0.314279	0.782389	0.40	0.688			
ACAT							
A2	0.935154	0.477533	1.96	<u>0.050</u>	2.55	1.00	6.50
A3	2.58210	0.601692	4.29	<u>0.000</u>	13.22	4.07	43.01
A4	2.09534	0.656289	3.19	<u>0.001</u>	8.13	2.25	29.42
E							
urban	-0.972296	0.414043	-2.35	<u>0.019</u>	0.38	0.17	0.85
T							
teaching	-0.809362	0.451149	-1.79	0.073	0.45	0.18	1.08
DC1	-29.7573	12.0665	-2.47	<u>0.014</u>	0.00	0.00	0.00
PM1	-14.6013	9.68042	-1.51	0.131	0.00	0.00	79.20
SQ1	6.44062	6.85358	0.94	0.347	626.80	0.00	2.7E7
OQ1	29.5432	9.39610	3.14	<u>0.002</u>	6.76E12	6.8E4	5.73E20
DI2	0.497894	4.94809	0.10	0.920	1.65	0.00	2.67E4
DM1	-5.22198	4.81772	-1.08	0.278	0.01	0.00	68.07

Log-Likelihood = -126.769

Test that all slopes are zero: G = 60.743, DF = 11, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	228.402	219	0.317
Deviance	253.539	219	0.055
Hosmer-Lemeshow	7.276	8	0.507

* * * MODEL 10 END * * *

Model 10 represents the logistic run of the predictors; irrespective of process step…the Full Model (all variables). There are 6 significant predictors from this Full Model that yielded a P-Value < 0.05; namely: ACAT (all 3 levels), Urban Environment, DC1, OQ1.

The next step is to run the regression again with only the significant variables to create a reduced model.

* * * MODEL 11 BEGIN * * *

Method: Binary Logistic Regression
Response Variable: Penalized (1 – Penalized, 0 – Not Penalized)
Model Inputs: ACAT E DC1 OQ1

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-0.456797	0.473158	-0.97	0.334			
ACAT							
A2	0.995189	0.420264	2.37	0.018	2.71	1.19	6.17
A3	2.53295	0.536886	4.72	0.000	12.59	4.40	36.06
A4	1.77119	0.476078	3.72	0.000	5.88	2.31	14.94
E							
urban	-1.04362	0.391753	-2.66	0.008	0.35	0.16	0.76
DC1	-32.7182	11.5356	-2.84	0.005	0.00	0.00	0.00
OQ1	21.9949	6.16011	3.57	0.000	3.5E09	2.0E4	6.2E14

Log-Likelihood = -131.297

Test that all slopes are zero: G = 51.689, DF = 6, P-Value = 0.000

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	147.398	146	0.452
Deviance	171.134	146	0.076
Hosmer-Lemeshow	6.999	8	0.537

* * * MODEL 11 END * * *

The reduced model yielded a result with all predictors being significant. The Reduced model represented by Model 11 is the final form for the equation that will used to predict Medicare penalties for this study. All predictors are significant and the Log-Likelihood value is -131.297, with a G statistic of 59.689 and a P-value = 0.000 which is less than 0.05. This confirms that the model is a good fit and is a statistically sound model to use for predictions. The statistical significance states that the parameter estimates are not equal to zero and will contribute to the model.

The Goodness of Fit tests (Pearson Test = 0.452, Hosmer-Lemeshow Test = 0.537), with the exception of Deviance (= 0.076), have statistic values high enough to conclude the model is acceptable. The Hosmer-Lemeshow expected and observed table shows how close the values were, and for the most part, they were fairly close to each other.

The concordant percentage is very high, approximately 75%, compared to the discordant percentage which is approximately 25%.

Although there is evidence that the estimated coefficient for Urban and DC1 are not zero, the odds ratio is very close to one and are very small, indicating that they will have a minimal effect on determining whether or not a hospital will be penalized.

Table 4.11 is the final logistic model in tabular form and it highlights the estimated coefficients and the odds ratios. The following general rule of thumb is a guide for interpreting the odds ratios. (Penn State)

- If odds equal to 1, "success" and "failure" are equally likely
- If odds > 1, then "success" is more likely than "failure"
- If odds < 1, then "success" is less likely than "failure"

- The odds of an A2 hospital being penalized compared to the odds of an A1 hospital being penalized are 2.71. A hospital with admissions in the 2000 to 6000 range will have a higher likelihood of receiving penalties, when compared to another hospital with fewer than 2000 annual admissions.

- The odds of an A3 hospital being penalized compared to the odds of an A1 hospital being penalized are 12.59. A hospital with admissions in the 5000 to 12000 range will have a higher likelihood of receiving penalties, when compared to another hospital with fewer than 2000 annual admissions. The apparent pattern is the higher the admission count, the higher the odds are for penalties.

- The odds of an A4 hospital being penalized compared to the odds of an A1 hospital being penalized are 5.88. A hospital with admissions greater than 12000 actually has a lower likelihood of being penalized, and this interesting because of the inverse relationship after the 12000 mark. Following the pattern of the previous two predictors (A2 and A3), where the odds were directly increasing with number admissions, it would be expected for the odds to continue to rise; however, that is not the case. The odds decreased instead. This potentially signifies that there could be a diminishing effect, in terms of the likelihood of being penalized, when the number of patient admissions increases.

- The odds of an urban hospital being penalized compared to the odds of a rural hospital being penalized are 0.35. This means that an urban hospital has a 35% greater chance of receiving penalties over the urban hospitals.

- The odds ratios for DC1 and OQ1 are extreme values. Further investigation is needed and will be a candidate for future work.

Table 4.11: Model Form Based of Final Logistic Model – PRE WALD TEST

Model Variable	**Variable Description**	**Estimated Coefficients**	**Odds Ratios**
Constant	Constant Term	-0.456797	
A2	Hospital Admissions [1811 – 5695]	0.995189	2.71
A3	Hospital Admissions [5696 – 11694]	2.53295	12.59
A4	Hospital Admissions > 11694	1.77119	5.88
E (Urban)	Hospitals in Urban Environments	-1.04362	0.35
DC1	Doctors Sometimes/Never Communicated to Patient	-32.7182	0.00
OQ1	Overall Quality Rating of 6 or Lower	21.9949	3.6E09

The final check of the model required the calculation of the univariate Wald test statistics, see Table 4.12. Mathematically speaking, this is the quotient of the regression coefficient and its standard error ($W_j = \hat{b}_j/\mathrm{se}(\hat{b}_j)$).

Table 4.12: Wald Test on Univariates of the Final Logistic Model

Model Variable	Estimated Coefficients	Standard Error (se) Coefficients	Wald Statistic
Constant	-0.456797	0.473158	-0.96542
A2	0.995189	0.420264	2.36801
A3	2.53295	0.536886	4.71785
A4	1.77119	0.476078	3.72038
E (Urban)	-1.04362	0.391753	-2.66397
DC1	-32.7182	11.5356	-2.83628
OQ1	21.9949	6.16011	3.57054

The Wald test statistic gives an indication of which variables are significant and which are not significant. A Wald critical value of 2 is equivalent to an approximate level of significance = 0.05. The completion of the test requires taking the absolute value of the Wald statistic. Based on the results of the Wald test, it is determined and confirmed that all the predictors are significant, and the model form in Table 4.11 will be considered the final predictor model.

4.10 Logistic Regression Model Form for Predicting Medicare Penalties

The dependence of the probability of being penalized on explanatory variables is modeled as follows:

$$\text{Logit}(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) \qquad (1)$$

Variable Definition: $\pi = the\ event\ probability$

$(Probability\ of\ being\ Penalized\ by\ Medicare)$

The Logit transformation of π_i converts the expression to a linear model.

$$\text{logit}(\pi\quad) = \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \sum_{i=1}^{m} \beta_i\ x_i \tag{2}$$

Variable Definition:

β_0 $-$ *the intercept term in the model*

i $-$ *index*

m $-$ *number of predictors in model*

β $-$ *the estimated parameters in model*

$$\text{Logit}(\pi) = \beta_0 + \sum_{i=1}^{m} \beta_i\ x_i = \hat{b}_0 + \hat{b}_1 x_1 + \hat{b}_2 x_2 + \hat{b}_3 x_3 \tag{3}$$

Assumption: Let p(x) = Logit (π)

Actual Linear Form of Model for Penalty Prediction

$\hat{p}$*(x) = -0.456797 + 0.995189*A2 + 2.53295*A3 + 1.77119*A4 - 1.04362*E*

*- 32.7182*DC1 + 21.9949*OQ1*

4.11 Logistic Regression Predictions

4.11.1 Sample Calculation of Event Probability

Definitions of Reference Events

- Event Definition: Hospital Penalized (Event = 1)
- ACAT: (A1)
- E (Rural)
- DC1 (Continuous)
- OQ1 (Continuous)

Event Probability ($\hat{\pi}$)

$$\hat{\pi} = \frac{e^{-0.456797+0.995189*A2+2.53295*A3+1.77119*A4-1.04362*E-32.7182*DC1+21.9949*OQ1}}{1+e^{-0.456797+0.995189*A2+2.53295*A3+1.77119*A4-1.04362*E-32.7182*DC1+21.9949*OQ1}}$$

Sample Calculation

The following data (Row 25) was extracted from calculated results (See Appendix B)

New Obs	Prob	SE Prob	95% CI
25	0.169905	0.056022	(0.085894, 0.308365)

The event probability, labeled as “Prob” was generated using the raw data and the event probability equation above. The inputs for the formula to calculate the event probabilities were actually from the original dataset that was used to construct the model. Appendix C shows the raw data inputs for these calculations.

	New Obs	ACAT	E	DC1	OQ1
Formula Inputs:	25	A1	urban	0.05	0.07

$\hat{\pi} \approx$

$$\frac{e^{-0.456797+0.995189*(0)+2.53295*(0)+1.77119*(0)-1.04362*(1)-32.7182*(0.05)+21.9949*(0.07)}}{1+e^{-0.456797+0.995189*(0)+2.53295*(0)+1.77119*(0)-1.04362*(1)-32.7182*(0.05)+21.9949*(0.07)}}$$

$$\hat{\pi} \approx \frac{0.202567118}{1+0.202567118} \approx 0.1684455$$

NOTE: small variation from system-generated value, Δ = 0.001

Interpretation of calculated event probability: 0.16844 is approximately 16.8%. The probability of an Urban hospital with Admissions with up to 1811 Admissions per year, a Doctor Communication annual 5% rating of poor communication and an Overall Quality rating = 7% is equal to 16.8%. Considering that this is on the low side (less than 50%, which is the generally accepted cutoff point), it will be in the Group Membership of No Penalties. In actuality, this particular hospital was not penalized, as was predicted, so it the model was correct with its prediction.

As was previously mentioned, in this study, the cutoff point for determining Group Membership (which Event the data will be placed), will be the same as the generally industry value of 0.5. This means that an event probability that is larger than 50% will be classified as an Event 1 (Penalized), and if it is smaller than 50%, it will be classified as an Event 2 (Not Penalized).

4.11.2 Classification Tables and ROC

Two classification tables were constructed. The first table consisted of the classification of the original data that was used to create the model. The goal was to determine how well the model could classify them. The second table is the classification of the Model Validation data. This is the data that was randomly pulled to test the model and its ability to predict outcome accurately.

4.11.2.1 Classification Table and ROC Graph - Model Formation Data

The classification table shown in Table 4.13 summarizes the results of using the Model Formation data to test the model. There were 111 hospitals that received Medicare penalties and the event probability was greater than 0.5; the classification was accurate. There were 51 hospitals that did not receive Medicare penalties and the event probability was greater than 0.5; the classification was accurate. However, there were also 23 hospitals that were not penalized, and the model classified them incorrectly, and counted them as getting penalized. Also, there were 47 hospitals that were not penalized, but the model incorrectly classified them as penalized hospitals.

Table 4.13: Classification Table based on Model Formation Data. *Penalized is classified as '1' when the event probability for an observation is greater than or equal to 0.5.*

	Classification		
	Correct	Incorrect	Total
1	111	23	134
0	51	47	98
Total	162	70	232

There are two statistics that can be obtained from this data: Sensitivity and Specificity. Sensitivity measures how well the model predicts a penalized hospital that was actually penalized; i.e. accurately predicting Event 1 (Penalty), and Specificity measures how well the model predicts a non-penalized hospital that was actually not penalized; i.e. accurately predicting Event 2 (No Penalty). The higher the statistics are for both sensitivity and specificity, the better the model's ability to classify observations.

Sensitivity = P(Classified Penalized = 1 | Observed Penalized = 1)

Specificity = P(Classified Penalized = 0 | Observed Penalized = 0)

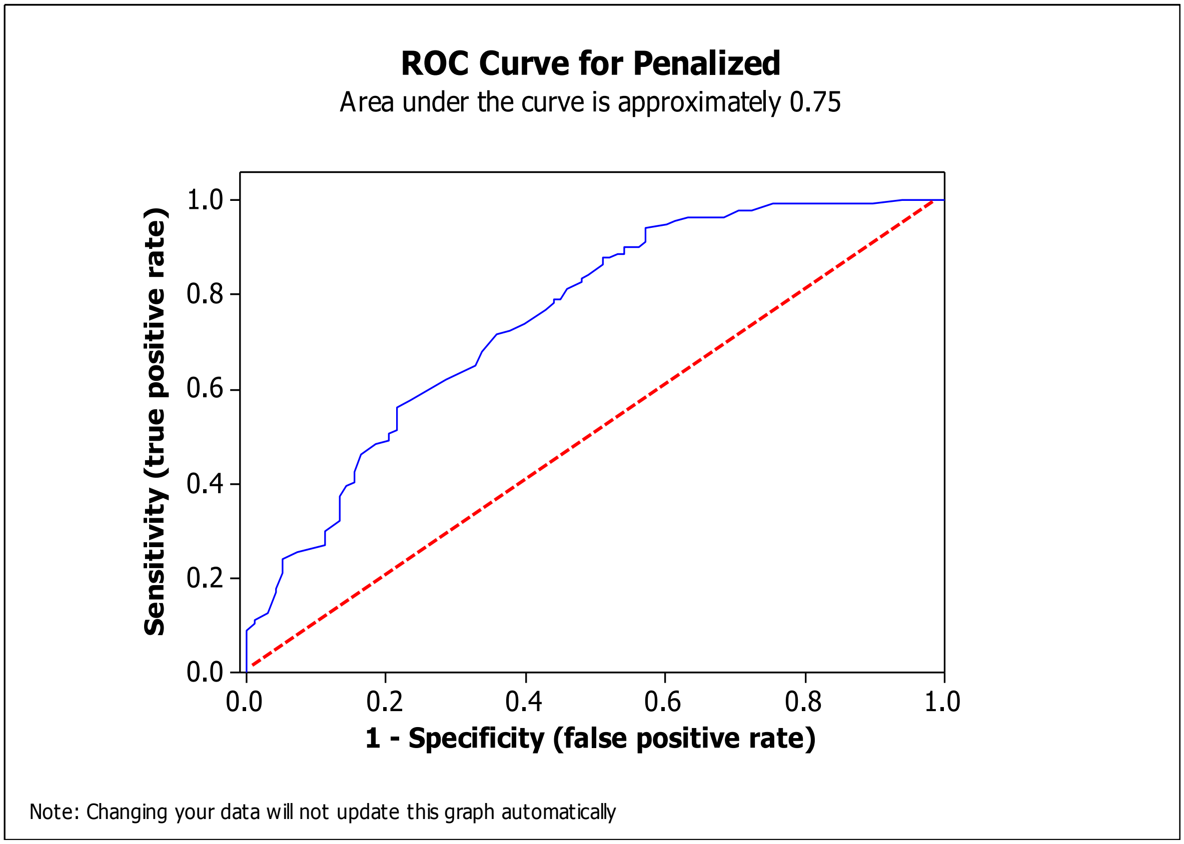


Figure 4.16: The Receiver Operating Characteristic (ROC) Curve for Model Formation Data

The ROC curve splits the graphical region into two domains, above the curve and below the curve. The area under the curve (AUC) is a measure of discrimination or an ability to classify events – in general. For this study, discrimination is defined as the ability of the test to correctly classify Penalized and Non-Penalized hospital.

If the AUC is large, the ROC curve is deemed to be reliable and is capable of predicting a correct response. Predication accuracy is reduced as the ROC curve approaches the 45° diagonal (red line) in the ROC space (Park). Figure 4.16 shows the resulting ROC curve for the model formation data. The AUC is estimated to be 0.75, which is an acceptable determination level for model reliability.

4.11.2.2 Classification Table and ROC Graph Based on Model Validation Data

The classification table shown in Table 4.14 summarizes the results of using the Model Validation data to test the model. There were 28 hospitals that received Medicare penalties and the event probability was greater than 0.5; the classification was accurate. There were 11 hospitals that did not receive Medicare penalties and the event probability was greater than 0.5; the classification was accurate. However, there were 6 hospitals who were not penalized, and the model classified them incorrectly, and counted them as getting penalized. Also, there were 13 hospitals that were not penalized, but the model incorrectly classified them as penalized hospitals.

Table 4.14: Classification Table based on Model Validation Data. *Penalized is classified as '1' when the event probability for an observation is greater than or equal to 0.5.*

	Classification		
	Correct	Incorrect	Total
1	28	6	34
0	11	13	24
Total	39	19	58

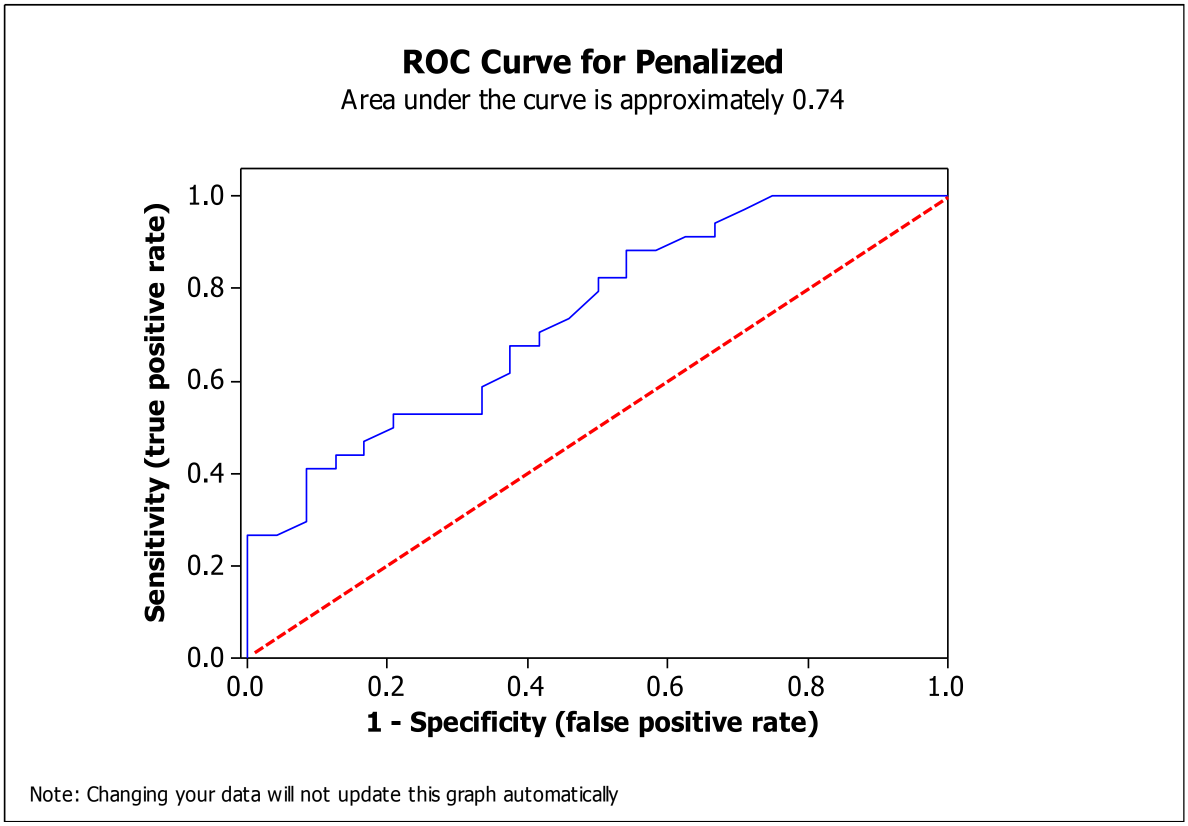


Figure 4.17: The Receiver Operating Characteristic (ROC) Curve for Model Validation Data

Hosmer and Lemeshow provide general rules for interpreting AUC values. Paraphrasing their rules gives the general guidelines below: (Minitab)

AUC = 0.5	No discrimination (i.e., might as well flip a coin)
0.7 ≤ AUC < 0.8	Acceptable discrimination
0.8 ≤ AUC < 0.9	Excellent discrimination
AUC ≥ 0.9	Outstanding discrimination (but extremely rare)

Based on the generally accepted AUC interpretations and viewing the ROC curves generated above, it is statistically sound to conclude that the final model generated from this study yields acceptable discrimination. Both ROC curves (data formation and data validation) resulted in AUC values that were comparable to each, with a delta of 0.01 or 1% deviation.

The data formation ROC curve has a discrimination value of 75%, which can be interpreted to mean that the model will correctly predict events 75% of the time. This is not perfect, but it is acceptable. The data validation ROC curve has a discrimination value of 74%, which is, for the most part basically equivalent to the data formulation value, considering that both 74% and 75% are within the same range, per Hosmer and Lemeshow.

CHAPTER 5

CONTRIBUTION TO THE BODY OF KNOWLEDGE

This project has intellectual merit and research relevance to the Body of Knowledge of Industrial Engineering in the following ways:

- Quality Assurance: This project will enable healthcare facilities to identify weaknesses in their operations and poor quality processes that lead to high hospital readmission rates.

- Work Measurement and Methods: To address the quality issues that exist, the operations will have to standardize their work processes and create a more connected enterprise that adequately manages patient care through the entire process.

- Economics: A key driver is economics…Medicare and hospitals have limited resources, and all operations are seeking ways to cut costs. The project seeks to minimize cost and improve quality healthcare services.

The characterization of the hospitals that were penalized provides useful information to the healthcare industry. The ability to use readily available data to quantify the likelihood of being penalized in the future by Medicare will allow hospitals to implement action plans and improvement initiatives in the vulnerable areas of their operations. The model can be used on an ongoing basis to assess monthly progress or status. The readmission problem is an expensive challenge on all fronts, and data explorations are needed from various angles to obtain viable and sound recommendations for solutions.

As stated before, the access to information in the healthcare industry is very limited due to the privacy and disclosure policies in place, as a result of this, it is a very difficult venture to obtain specific information about things of interest within this industry.

The fundamental goal of this project was to use the healthcare information that is in the public domain and explore the possibility of creating a model to predict a hospital being penalized. This was achieved. The final model that was constructed was deemed to be acceptable. It should be iterated that the focus of this project was the hospitals in Texas, so in rephrasing the prior statement, the key output of this research is an acceptable predictive model for determining if a Texas hospital would be penalized.

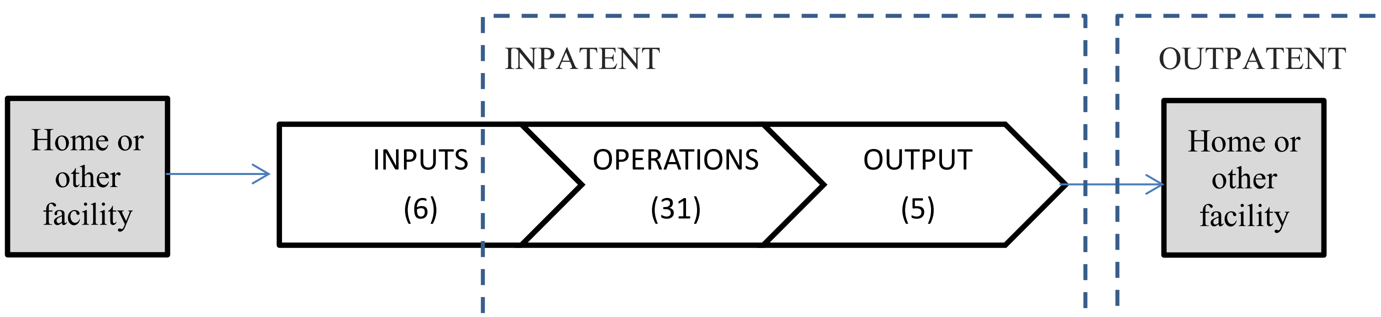
This is vital information for the healthcare industry in Texas. This public information is still accessible, and considering the next wave of penalties is coming up in October, it would be imperative for hospitals to start making plans for what could potentially impact them. This model, with 75% accuracy, could help them see the need to accelerate their efforts to bring change to their operations to reduce hospital readmission rates.

CHAPTER 6

CONCLUSION

This project started with a careful literature-based approach to selecting a variety of potentially meaningful independent variables to use in an analysis that would seek to create a statistically sound model for making Medicare penalty predictions.

The initial count of independent variables was 42 (6 – inputs, 31 – operations, 5 - output). These variables were categorized according to a very generic process: INPUTS >> OPERATIONS >> OUTPUTS.

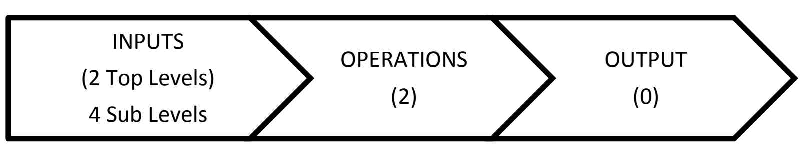


The healthcare system is in a state in which patient care can end up becoming a never-ending loop, where the patient is continuously cycling though the process steps for various reasons, and some measure of blame resides with the patient. However, the issue of a “revolving door" patient has become a national priority and a national issue primarily due to the costs involved.

The Medicare penalties were installed to motivate hospitals to get up close and personal with their procedures and policies to see what is happening, or what is not happening for that matter – the goal is to determine what is contributing to this revolving door phenomenon. As was stated very early on, the Medicare program was initially designed to help the seniors or other vulnerable individuals in our society, but it has slowly decayed into a cavity that seems to be impossible "to fill or even extract". If nothing is done, if no action is made to improve the health of the "tooth", eventually it will just simply decay to the point where it is beyond repair – remember there is still pain with a decayed tooth.

As a reminder, the Medicare penalties that will be issued in October will increase 1%, and the maximum penalty that could be assessed will be 2%. These penalties are here to stay.

The statistical processes and tools were utilized and the data was analyzed, the resulting model is deemed to be accurate, with a 75% AUC discrimination value – this model is certainly statistically capable of helping hospitals understand their position with respect to being penalized. The model variable count was reduced from 42 to 6 vital predictors. There were 2 main variables from the Input process step, but was further sub-divided for the analysis: (Admissions: A2, A3, A4, Urban Environment), and 2 variables from the Operations process step (Doctor's Communication - DC1 and Overall Quality rating (OQ1).



Interestingly enough, there were no significant predictors from the Output process step, and it is interesting because much can be done at that phase to help prepare the patient for surviving on the outside after being discharged. The things they do or do not do will have an impact, and if things are done correctly, from the patient and the healthcare system standpoint, 30 day readmission rates will decline.

6.1 Revisiting Research Objectives

The objectives of this dissertation can be summarized with these main questions:

RESEARCH QUESTION #1: DATA COLLECTION**:** Of data available, what key determining characteristics or parameters can define the Texas hospitals that were penalized? Where do these characteristics fit in the overall enterprise or systems process view of healthcare services?

SYSTEM: Inputs >>> Internal Operations >>> Outputs

QUESTION #1 RESPONSE:

- *What key determining characteristics or parameters can define the Texas hospitals that were penalized?*
    - Admissions
    - Environment
    - Doctor Communication
    - Overall Hospital Quality Ranking
- *Where do these characteristics fit in the overall enterprise or systems process view of healthcare services?*

- Input Process Step: Admissions, Environment
- Operations Process Step: Doctor Communication, Overall Hospital Quality Ranking

RESEARCH QUESTION #2: ANALYSES: Can a predictive model be established using statistical or simulation techniques to assist hospitals with determining their “penalty potential status”?

QUESTION #2 RESPONSE

- *Can a predictive model be established using statistical techniques to assist hospitals with determining their “penalty potential status”?*

  Yes, the model generated has a discrimination value = .75, and industry standards deemed this model to be acceptable for making predictions about future penalties. However, the application of the model is limited to Texas hospitals only.

- *Can a predictive model be established using simulation techniques to assist hospitals with determining their “penalty potential status”?*

  In consulting with an expert in the field of simulation, and conducting literature searches, the use of simulation techniques and software in the manner that is required by this study, would not be feasible. Simulation requires critical inputs such as distributions, and distributions statistics are not typically established for surveyed information. The development of reliable and statistically proven distributions for each variable used would require several years, considering the survey data is published annually.

RESEARCH QUESTION #3: ACCESSIBILITY: Can the statistical model be converted to a format that is interactive?

QUESTION #3 RESPONSES: Absolutely. Four of the predictor variables are from the Input process: Admissions and Environment. It should be noted that although there are 3 admissions variables, there is only one admission value to consider. The environment variable will most likely not change simply due to the physical constraints. The doctor communication ranking and overall quality rate is information that is collected by various organizations; however, the data dispersed by CMS will be best to use. A website dedicated to making predictions or an I-phone app can be constructed based on the model. The actual construction of these interactive tools was outside the scope of this research, but the answer to the question is yes, it is possible to make this information accessible via an interactive format.

6.2 Future Work

This project has unveiled many things that could be done in the future for enhancement and further development.

- *Discharge Processes* – an extensive study needs to be done to see what specific things are being done to help the patient when they leave the hospital. Are they being prepared before they leave? Are they being trained to take care of themselves on the outside? Is there a follow-up procedure in place at the hospital, where a patient is contacted within a certain timeframe? Are primary care physicians in the communication loop? What are hospitals who were not penalized doing to avoid readmissions? What is working for them in terms of communication (inside and outside the hospital)? What special programs are in place to help with care transition process?

- Systems – the determination of current discharge procedures can lead to the development of a systems view on how things are done. Once this is established, the overall system can be examined for opportunities for improvement. Communication across the entire system is key, and a careful look on what tools and resources are tasked with communicating would be essential to determine.

- *Interactive Tool* – research the software/website development process. Speak to hospital administrators about the potentials of an interactive tool.

- *ROC Curve* – test models using various event probabilities. (0.5 used in study).

- *Categorizing Operations Data:* Compile the continuous data in the operations step and run the analysis to see if other variables will be classified as statistically significant and to see if the discrimination could be improved.

APPENDIX A

TITLES TO THE AFFORDABLE CARE ACT

APPENDIX A

- Title I. Quality, Affordable Health Care for All Americans
- Title II. The Role of Public Programs
- Title III. Improving the Quality and Efficiency of Health Care
- Title IV. Prevention of Chronic Disease and Improving Public Health
- Title V. Health Care Workforce
- Title VI. Transparency and Program Integrity
- Title VII. Improving Access to Innovative Medical Therapies
- Title VIII. Community Living Assistance Services and Supports Act (CLASS Act)
- Title IX. Revenue Provisions
- Title X. Reauthorization of the Indian Health Care Improvement Act

Source: Health and Human Service Website. http://www.healthcare.gov/law/index.html

APPENDIX B

PREDICTED EVENT PROBABILITIES BASED ON MODEL CONSTRUCTION DATASET

APPENDIX B

TITLE: Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	9818	74.8	Somers' D	0.50
Discordant	3255	24.8	Goodman-Kruskal Gamma	0.50
Ties	59	0.4	Kendall's Tau-a	0.24
Total	13132	100.0		

Predicted Event Probabilities for New Observations

New Obs	Prob	SE Prob	95% CI
1	0.469436	0.082356	(0.316372, 0.628474)
2	0.301581	0.071190	(0.182094, 0.455782)
3	0.793457	0.062089	(0.646417, 0.889775)
4	0.556085	0.075264	(0.407988, 0.694843)
5	0.281061	0.066319	(0.170445, 0.426551)
6	0.320210	0.098513	(0.162490, 0.533501)
7	0.325734	0.083557	(0.186458, 0.504527)
8	0.670074	0.095389	(0.465764, 0.825519)
9	0.238063	0.059636	(0.140914, 0.373101)
10	0.137562	0.046706	(0.068671, 0.256530)
11	0.298964	0.088449	(0.157178, 0.493727)
12	0.556085	0.075264	(0.407988, 0.694843)
13	0.620692	0.093431	(0.429151, 0.780793)
14	0.852900	0.052010	(0.720112, 0.928908)
15	0.545225	0.116370	(0.323343, 0.750493)
16	0.562587	0.109308	(0.350024, 0.754410)
17	0.799132	0.064774	(0.643362, 0.897686)
18	0.791592	0.065000	(0.636988, 0.891561)
19	0.829167	0.061189	(0.675480, 0.918818)
20	0.300763	0.131065	(0.112530, 0.593346)
21	0.059760	0.045251	(0.012942, 0.235525)
22	0.586613	0.069570	(0.447121, 0.713464)
23	0.233511	0.067429	(0.127086, 0.389310)
24	0.184391	0.053910	(0.100701, 0.313396)
25	0.169905	0.056022	(0.085894, 0.308365)
26	0.856041	0.053244	(0.718286, 0.932743)
27	0.137562	0.046706	(0.068671, 0.256530)
28	0.344160	0.108968	(0.169240, 0.574785)
29	0.598686	0.093443	(0.410408, 0.761745)
30	0.238063	0.059636	(0.140914, 0.373101)
31	0.166371	0.050337	(0.089242, 0.289007)
32	0.500292	0.081289	(0.346123, 0.654405)
33	0.571534	0.123647	(0.331476, 0.782065)
34	0.708128	0.081191	(0.529061, 0.839733)
35	0.610498	0.070467	(0.467194, 0.736960)
36	0.137562	0.046706	(0.068671, 0.256530)
37	0.306929	0.075002	(0.181598, 0.469171)
38	0.772470	0.071524	(0.604612, 0.882872)
39	0.749814	0.070583	(0.589083, 0.862364)
40	0.254197	0.086510	(0.122310, 0.454632)
41	0.408108	0.097527	(0.238101, 0.603372)
42	0.639709	0.066709	(0.501705, 0.757932)
43	0.562312	0.075324	(0.413553, 0.700651)
44	0.500292	0.081289	(0.346123, 0.654405)
45	0.616489	0.072532	(0.468391, 0.745727)
46	0.844988	0.075285	(0.638600, 0.943871)
47	0.256565	0.064285	(0.151296, 0.400513)
48	0.793457	0.062089	(0.646417, 0.889775)
49	0.242676	0.070060	(0.131791, 0.403498)
50	0.556085	0.075264	(0.407988, 0.694843)
51	0.306929	0.075002	(0.181598, 0.469171)
52	0.586613	0.069570	(0.447121, 0.713464)
53	0.420368	0.097876	(0.248137, 0.614447)
54	0.710466	0.065187	(0.568698, 0.820355)
55	0.103471	0.041624	(0.045709, 0.217586)
56	0.756115	0.080476	(0.568602, 0.879408)
57	0.238063	0.059636	(0.140914, 0.373101)
58	0.126185	0.045386	(0.060547, 0.244464)
59	0.349630	0.106067	(0.177278, 0.572870)
60	0.870263	0.054657	(0.722016, 0.945426)
61	0.809449	0.069268	(0.637895, 0.911058)
62	0.637091	0.101399	(0.426337, 0.805704)
63	0.126185	0.045386	(0.060547, 0.244464)
64	0.397282	0.103883	(0.219751, 0.606712)
65	0.123426	0.046822	(0.056862, 0.247465)
66	0.717610	0.083741	(0.530639, 0.851013)
67	0.705473	0.071895	(0.548676, 0.825156)

68	0.723216	0.086198	(0.529088, 0.858691)
69	0.444767	0.087974	(0.284946, 0.616894)
70	0.572885	0.092348	(0.390294, 0.737563)
71	0.517371	0.089629	(0.346600, 0.684179)
72	0.180622	0.054414	(0.096847, 0.311843)
73	0.137562	0.046706	(0.068671, 0.256530)
74	0.208017	0.082444	(0.089664, 0.411906)
75	0.639709	0.066709	(0.501705, 0.757932)
76	0.126185	0.045386	(0.060547, 0.244464)
77	0.461425	0.087114	(0.301185, 0.630053)
78	0.436830	0.092937	(0.270031, 0.619256)
79	0.624728	0.113901	(0.391131, 0.811821)
80	0.149789	0.050528	(0.074890, 0.277154)
81	0.261414	0.066346	(0.152887, 0.409717)
82	0.275984	0.073679	(0.156148, 0.439851)
83	0.654058	0.095570	(0.452413, 0.812262)
84	0.475454	0.079750	(0.326293, 0.629128)
85	0.400353	0.090056	(0.242463, 0.582060)
86	0.643804	0.100045	(0.434589, 0.809533)
87	0.153035	0.049382	(0.078876, 0.276023)
88	0.254197	0.086510	(0.122310, 0.454632)
89	0.199816	0.054479	(0.113521, 0.327475)
90	0.281061	0.066319	(0.170445, 0.426551)
91	0.633865	0.077046	(0.474563, 0.768437)
92	0.347938	0.089493	(0.197621, 0.536188)
93	0.180622	0.054414	(0.096847, 0.311843)
94	0.639709	0.066709	(0.501705, 0.757932)
95	0.525127	0.088544	(0.355411, 0.689231)
96	0.803157	0.072794	(0.623327, 0.909587)
97	0.338480	0.092651	(0.185265, 0.535173)
98	0.772274	0.066649	(0.617374, 0.876962)
99	0.598686	0.093443	(0.410408, 0.761745)
100	0.458243	0.099903	(0.277651, 0.650515)
101	0.543856	0.098574	(0.353675, 0.722054)
102	0.322927	0.081114	(0.187327, 0.496692)
103	0.580745	0.076058	(0.428880, 0.718713)
104	0.764463	0.122559	(0.460889, 0.924935)
105	0.700197	0.084201	(0.515516, 0.836770)
106	0.749814	0.070583	(0.589083, 0.862364)
107	0.137562	0.046706	(0.068671, 0.256530)
108	0.345038	0.095318	(0.187306, 0.546308)
109	0.628243	0.079941	(0.463523, 0.767731)
110	0.550116	0.078252	(0.396859, 0.694417)
111	0.725703	0.074479	(0.559613, 0.846351)
112	0.519102	0.088198	(0.350686, 0.683287)
113	0.725703	0.074479	(0.559613, 0.846351)
114	0.787394	0.065179	(0.633249, 0.888191)
115	0.562587	0.109308	(0.350024, 0.754410)
116	0.765773	0.075570	(0.588755, 0.881881)
117	0.251776	0.079960	(0.127742, 0.436038)
118	0.550116	0.078252	(0.396859, 0.694417)
119	0.759173	0.097362	(0.526078, 0.899519)
120	0.785241	0.075609	(0.602937, 0.898003)
121	0.580745	0.076058	(0.428880, 0.718713)
122	0.844988	0.075285	(0.638600, 0.943871)
123	0.469436	0.082356	(0.316372, 0.628474)
124	0.503773	0.133500	(0.262776, 0.743030)
125	0.598686	0.093443	(0.410408, 0.761745)
126	0.519102	0.088198	(0.350686, 0.683287)
127	0.620692	0.093431	(0.429151, 0.780793)
128	0.361087	0.089827	(0.208534, 0.547974)
129	0.286194	0.079260	(0.157842, 0.461697)
130	0.765773	0.075570	(0.588755, 0.881881)
131	0.803563	0.066451	(0.641899, 0.903245)
132	0.725703	0.074479	(0.559613, 0.846351)
133	0.919078	0.037883	(0.807142, 0.968575)
134	0.574581	0.083674	(0.408456, 0.725416)
135	0.251776	0.079960	(0.127742, 0.436038)
136	0.811417	0.066718	(0.646726, 0.910014)
137	0.580745	0.076058	(0.428880, 0.718713)
138	0.550116	0.078252	(0.396859, 0.694417)
139	0.919078	0.037883	(0.807142, 0.968575)
140	0.803563	0.066451	(0.641899, 0.903245)
141	0.723216	0.086198	(0.529088, 0.858691)
142	0.836557	0.058739	(0.688008, 0.922359)
143	0.436830	0.092937	(0.270031, 0.619256)
144	0.283656	0.084675	(0.148914, 0.472615)
145	0.461425	0.087114	(0.301185, 0.630053)
146	0.597019	0.090508	(0.414772, 0.755911)
147	0.911368	0.040031	(0.795620, 0.964490)
148	0.331308	0.087422	(0.186080, 0.517775)
149	0.843349	0.060341	(0.687437, 0.929469)
150	0.826162	0.058715	(0.680784, 0.913723)
151	0.871356	0.096668	(0.555462, 0.973487)
152	0.353692	0.083628	(0.210839, 0.528513)
153	0.840723	0.093672	(0.572627, 0.954116)
154	0.632514	0.114082	(0.396772, 0.818314)
155	0.852900	0.052010	(0.720112, 0.928908)
156	0.461425	0.087114	(0.301185, 0.630053)
157	0.760743	0.073481	(0.590370, 0.875231)
158	0.542135	0.088429	(0.370683, 0.704156)
159	0.517371	0.089629	(0.346600, 0.684179)
160	0.814619	0.061580	(0.663981, 0.907167)
161	0.946345	0.027957	(0.857038, 0.981094)
162	0.713322	0.095446	(0.499194, 0.861329)
163	0.818404	0.063528	(0.661004, 0.912406)
164	0.654058	0.095570	(0.452413, 0.812262)
165	0.418282	0.130907	(0.200322, 0.673624)
166	0.382688	0.090081	(0.226967, 0.566897)
167	0.893538	0.047802	(0.758141, 0.957397)
168	0.778369	0.070161	(0.612790, 0.886282)
169	0.824998	0.092754	(0.572341, 0.943201)
170	0.945048	0.028952	(0.852220, 0.980875)
171	0.733216	0.082055	(0.547067, 0.862140)
172	0.814619	0.061580	(0.663981, 0.907167)
173	0.795046	0.070032	(0.625569, 0.900067)
174	0.915040	0.038561	(0.802915, 0.966071)
175	0.826162	0.058715	(0.680784, 0.913723)
176	0.778369	0.070161	(0.612790, 0.886282)
177	0.760743	0.073481	(0.590370, 0.875231)
178	0.722702	0.091567	(0.515588, 0.864530)
179	0.778369	0.070161	(0.612790, 0.886282)
180	0.873089	0.048413	(0.745015, 0.941854)
181	0.782697	0.071407	(0.612678, 0.891322)
182	0.895918	0.043203	(0.776365, 0.955243)
183	0.846112	0.054434	(0.707866, 0.925794)
184	0.922458	0.037198	(0.811068, 0.970559)
185	0.858618	0.053760	(0.718266, 0.935344)
186	0.829167	0.061189	(0.675480, 0.918818)
187	0.670074	0.095389	(0.465764, 0.825519)
188	0.647733	0.102721	(0.432108, 0.816294)
189	0.782697	0.071407	(0.612678, 0.891322)
190	0.846112	0.054434	(0.707866, 0.925794)
191	0.799132	0.064774	(0.643362, 0.897686)
192	0.760743	0.073481	(0.590370, 0.875231)
193	0.846112	0.054434	(0.707866, 0.925794)
194	0.586613	0.069570	(0.447121, 0.713464)
195	0.667920	0.070903	(0.518055, 0.790067)
196	0.935305	0.036062	(0.818036, 0.978944)
197	0.760743	0.073481	(0.590370, 0.875231)
198	0.556085	0.075264	(0.407988, 0.694843)
199	0.450738	0.084196	(0.296454, 0.615115)
200	0.883703	0.047461	(0.754517, 0.949459)
201	0.592725	0.084088	(0.423732, 0.742300)
202	0.756115	0.080476	(0.568602, 0.879408)
203	0.415564	0.121911	(0.210016, 0.655389)

204	0.372563	0.096211	(0.209504, 0.570881)
205	0.500292	0.081289	(0.346123, 0.654405)
206	0.886275	0.045984	(0.761161, 0.950142)
207	0.639709	0.066709	(0.501705, 0.757932)
208	0.735428	0.064412	(0.592306, 0.841732)
209	0.616489	0.072532	(0.468391, 0.745727)
210	0.475454	0.079750	(0.326293, 0.629128)
211	0.735428	0.064412	(0.592306, 0.841732)
212	0.710466	0.065187	(0.568698, 0.820355)
213	0.633865	0.077046	(0.474563, 0.768437)
214	0.869160	0.056367	(0.715465, 0.946091)
215	0.758968	0.068746	(0.601206, 0.868021)
216	0.639709	0.066709	(0.501705, 0.757932)
217	0.396084	0.088890	(0.240461, 0.576039)
218	0.667920	0.070903	(0.518055, 0.790067)
219	0.662292	0.067213	(0.521121, 0.779459)
220	0.586613	0.069570	(0.447121, 0.713464)
221	0.667920	0.070903	(0.518055, 0.790067)
222	0.610498	0.070467	(0.467194, 0.736960)
223	0.710466	0.065187	(0.568698, 0.820355)
224	0.481759	0.090057	(0.314326, 0.653391)
225	0.633865	0.077046	(0.474563, 0.768437)
226	0.662292	0.067213	(0.521121, 0.779459)
227	0.531423	0.074064	(0.387676, 0.670138)
228	0.662292	0.067213	(0.521121, 0.779459)
229	0.633865	0.077046	(0.474563, 0.768437)
230	0.562312	0.075324	(0.413553, 0.700651)
231	0.694975	0.080182	(0.520523, 0.827045)
232	0.689594	0.065231	(0.550067, 0.801469)

APPENDIX C

VALUES OF PREDICTORS FOR NEW OBSERVATIONS (INPUTS FOR EVENT PROBABILITIES)

APPENDIX C

New Obs	ACAT	E	DC1	OQ1
1	A1	rural	0.03	0.06
2	A1	urban	0.02	0.06
3	A4	urban	0.04	0.11
4	A4	urban	0.04	0.06
5	A1	urban	0.03	0.07
6	A2	urban	0.02	0.02
7	A2	urban	0.04	0.05
8	A3	urban	0.05	0.06
9	A1	urban	0.03	0.06
10	A1	urban	0.03	0.03
11	A2	urban	0.03	0.03
12	A4	urban	0.04	0.06
13	A2	urban	0.03	0.09
14	A2	rural	0.03	0.10
15	A1	urban	0.03	0.12
16	A1	rural	0.06	0.12
17	A3	urban	0.05	0.09
18	A2	rural	0.05	0.11
19	A3	urban	0.03	0.07
20	A1	rural	0.08	0.10
21	A1	urban	0.10	0.09
22	A4	urban	0.05	0.08
23	A1	urban	0.01	0.03
24	A1	urban	0.04	0.06
25	A1	urban	0.05	0.07
26	A2	rural	0.05	0.13
27	A1	urban	0.03	0.03
28	A1	rural	0.06	0.08
29	A1	rural	0.00	0.04
30	A1	urban	0.03	0.06
31	A1	urban	0.03	0.04
32	A4	urban	0.04	0.05
33	A2	rural	0.02	0.02
34	A2	rural	0.05	0.09
35	A4	urban	0.04	0.07
36	A1	urban	0.03	0.03
37	A1	urban	0.04	0.09
38	A1	rural	0.03	0.12
39	A1	rural	0.02	0.10
40	A2	urban	0.03	0.02
41	A1	rural	0.01	0.02
42	A4	urban	0.05	0.09
43	A4	urban	0.06	0.09
44	A4	urban	0.04	0.05
45	A4	urban	0.06	0.10
46	A1	rural	0.05	0.17
47	A1	urban	0.02	0.05
48	A4	urban	0.04	0.11
49	A1	urban	0.05	0.09
50	A4	urban	0.04	0.06
51	A1	urban	0.04	0.09
52	A4	urban	0.05	0.08
53	A1	rural	0.05	0.08
54	A4	urban	0.04	0.09
55	A1	urban	0.04	0.03
56	A3	urban	0.03	0.05
57	A1	urban	0.03	0.06
58	A1	urban	0.04	0.04
59	A4	urban	0.08	0.08
60	A3	urban	0.02	0.07
61	A1	rural	0.03	0.13
62	A2	rural	0.06	0.09
63	A1	urban	0.04	0.04
64	A1	urban	0.00	0.05
65	A1	urban	0.02	0.01
66	A3	urban	0.05	0.07
67	A1	rural	0.02	0.09
68	A2	rural	0.02	0.05
69	A1	rural	0.04	0.07
70	A2	urban	0.05	0.11
71	A2	urban	0.05	0.10
72	A1	urban	0.02	0.03
73	A1	urban	0.03	0.03
74	A1	urban	0.07	0.11
75	A4	urban	0.05	0.09
76	A1	urban	0.04	0.04
77	A2	urban	0.05	0.09
78	A2	urban	0.06	0.10
79	A3	urban	0.07	0.08
80	A1	urban	0.02	0.02
81	A1	urban	0.04	0.08
82	A1	urban	0.01	0.04
83	A2	rural	0.03	0.05
84	A4	urban	0.05	0.06
85	A2	urban	0.03	0.05
86	A2	urban	0.02	0.08
87	A1	urban	0.04	0.05
88	A2	urban	0.03	0.02
89	A1	urban	0.03	0.05
90	A1	urban	0.03	0.07
91	A4	urban	0.03	0.06
92	A2	urban	0.03	0.04
93	A1	urban	0.02	0.03
94	A4	urban	0.05	0.09
95	A4	urban	0.03	0.04

96	A3	urban	0.07	0.12
97	A1	rural	0.04	0.05
98	A4	urban	0.03	0.09
99	A1	rural	0.00	0.04
100	A1	urban	0.02	0.09
101	A1	rural	0.00	0.03
102	A1	urban	0.01	0.05
103	A1	rural	0.03	0.08
104	A1	urban	0.02	0.15
105	A1	rural	0.00	0.06
106	A1	rural	0.02	0.10
107	A1	urban	0.03	0.03
108	A1	urban	0.00	0.04
109	A1	rural	0.01	0.06
110	A1	rural	0.02	0.06
111	A1	rural	0.01	0.08
112	A1	rural	0.01	0.04
113	A1	rural	0.01	0.08
114	A2	rural	0.03	0.08
115	A1	rural	0.06	0.12
116	A2	rural	0.02	0.06
117	A1	urban	0.00	0.02
118	A1	rural	0.02	0.06
119	A1	rural	0.06	0.16
120	A1	rural	0.00	0.08
121	A1	rural	0.03	0.08
122	A1	rural	0.05	0.17
123	A1	rural	0.03	0.06
124	A2	rural	0.07	0.08
125	A1	rural	0.00	0.04
126	A1	rural	0.01	0.04
127	A2	urban	0.03	0.09
128	A1	rural	0.03	0.04
129	A1	urban	0.05	0.10
130	A2	rural	0.02	0.06
131	A2	rural	0.02	0.07
132	A1	rural	0.01	0.08
133	A2	rural	0.03	0.13
134	A1	rural	0.01	0.05
135	A1	urban	0.00	0.02
136	A2	rural	0.06	0.13
137	A1	rural	0.03	0.08
138	A1	rural	0.02	0.06
139	A2	rural	0.03	0.13
140	A2	rural	0.02	0.07
141	A2	rural	0.02	0.05
142	A2	rural	0.02	0.08
143	A2	urban	0.06	0.10
144	A2	urban	0.06	0.07
145	A2	urban	0.05	0.09
146	A2	urban	0.04	0.10
147	A2	rural	0.04	0.14
148	A2	urban	0.06	0.08
149	A2	rural	0.06	0.14
150	A2	rural	0.05	0.12
151	A2	urban	0.09	0.24
152	A2	urban	0.05	0.07
153	A2	urban	0.07	0.20
154	A2	urban	0.07	0.15
155	A2	rural	0.03	0.10
156	A2	urban	0.05	0.09
157	A3	urban	0.05	0.08
158	A2	urban	0.04	0.09
159	A2	urban	0.05	0.10
160	A3	urban	0.04	0.08
161	A3	rural	0.05	0.11
162	A2	rural	0.07	0.12
163	A3	urban	0.06	0.11
164	A2	rural	0.03	0.05
165	A2	urban	0.00	0.01
166	A2	urban	0.06	0.09
167	A3	urban	0.02	0.08
168	A3	urban	0.04	0.07
169	A3	rural	0.07	0.08
170	A3	rural	0.03	0.08
171	A2	rural	0.06	0.11
172	A3	urban	0.04	0.08
173	A3	urban	0.03	0.06
174	A3	urban	0.04	0.12
175	A2	rural	0.05	0.12
176	A3	urban	0.04	0.07
177	A3	urban	0.05	0.08
178	A3	urban	0.07	0.10
179	A3	urban	0.04	0.07
180	A3	urban	0.04	0.10
181	A3	urban	0.06	0.10
182	A3	urban	0.04	0.11
183	A3	urban	0.04	0.09
184	A3	urban	0.03	0.11
185	A3	urban	0.03	0.08
186	A3	urban	0.03	0.07
187	A3	urban	0.05	0.06
188	A3	urban	0.06	0.07
189	A3	urban	0.06	0.10
190	A3	urban	0.04	0.09
191	A3	urban	0.05	0.09
192	A3	urban	0.05	0.08
193	A3	urban	0.04	0.09
194	A4	urban	0.05	0.08
195	A4	urban	0.06	0.11
196	A3	rural	0.07	0.13
197	A3	urban	0.05	0.08
198	A4	urban	0.04	0.06
199	A4	urban	0.06	0.07
200	A3	urban	0.03	0.09
201	A4	urban	0.07	0.11
202	A3	urban	0.03	0.05
203	A1	urban	0.06	0.14
204	A4	urban	0.07	0.07
205	A4	urban	0.04	0.05
206	A3	urban	0.05	0.12
207	A4	urban	0.05	0.09
208	A4	urban	0.05	0.11
209	A4	urban	0.06	0.10
210	A4	urban	0.05	0.06
211	A4	urban	0.05	0.11
212	A4	urban	0.04	0.09
213	A4	urban	0.03	0.06

214	A4	urban	0.03	0.12
215	A4	urban	0.06	0.13
216	A4	urban	0.05	0.09
217	A4	urban	0.06	0.06
218	A4	urban	0.06	0.11
219	A4	urban	0.04	0.08
220	A4	urban	0.05	0.08
221	A4	urban	0.06	0.11
222	A4	urban	0.04	0.07
223	A4	urban	0.04	0.09
224	A4	urban	0.07	0.09
225	A4	urban	0.03	0.06
226	A4	urban	0.04	0.08
227	A4	urban	0.05	0.07
228	A4	urban	0.04	0.08
229	A4	urban	0.03	0.06
230	A4	urban	0.06	0.09
231	A4	urban	0.07	0.13
232	A4	urban	0.05	0.10

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