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Strategies for Reducing Preventable Hospital Readmissions on Medicare Patients

Andres Patricio Garcia-Arce
University of South Florida, garciampu@gmail.com

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by

Andres Garcia-Arce

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Major Professor: José L. Zayas-Castro, Ph.D.
Jay Wolfson, Dr.P.H., J.D.
Peter Fabri, M.D.
Alex Savachkin, Ph.D.
Stephanie L. Carey, Ph.D.

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Dedication

To my family. To you, Yoyi.

Acknowledgment

I want to acknowledge my advisor Dr. José L. Zayas-Castro, for his professional and personal mentoring. I also want to thank Dr. Jaime Bustos for giving me a start. Moreover, I recognize the contribution from Dr. Jay Wolfson for providing an outstanding support. I thank the rest of the members of my doctoral committee: Dr. Peter Fabri, Dr. Alex Savachkin, and Dr. Stephanie L. Carey. Finally, I want to express my gratitude for the support and encouragement of my friends and colleagues in the program. Notably, to my partner and close friends, who heroically withstood the hardships of the program with me, this work would not have been without your unwavering support.

The journey continues.

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Abstract

The high expenditure of healthcare in the United States (U.S.) does not translate into better quality of care. Indeed, the U.S. healthcare system is recognized by its lack of efficiency and waste (which represents about 20% of the country's healthcare expenses). Lack of coordination is one of the most referenced causes of waste in the U.S. healthcare system, and preventable hospital readmissions have been acknowledged to be evidence of poor coordination of care. In fiscal year 2013, the Centers for Medicare and Medicaid Services (CMS) established financial penalties for inpatient care reimbursements in hospitals with excessive readmissions. All the same, the preliminary results of this effort have yet to result in a consistent reduction of readmission rates. Research in healthcare policy is usually reported through case studies, which makes it difficult to apply that research to different spatiotemporal contexts. Additionally, relevant research can remain overlooked due to the challenge of translating it from other fields. Therefore, in order to create effective healthcare policies, a system that can provide the most accurate information to stakeholders about their decisions and the future impact of those decisions should be developed.

This dissertation proposes a decision-based support system that could aid hospital administrators in the design of disease-specific interventions that target specific groups of patients who are at risk for readmission. First, the use of disease-specific interventions that were designed to reduce readmissions will be explored. Second, a variety of predictive tools for readmissions will be developed and compared to complete the search for the best tool. Finally, an optimization model bringing together the two ideas will be formulated so that hospitals can use it to design interventions. This model will target specific patients depending on their risk for readmission and minimize the cost of intervention while ensuring quality hospital performance. In sum, this

work will help hospital administrators to better plan in the reduction of readmissions and in the implementation of interventions. In addition, it will deepen knowledge about the impacts of economic penalties on hospitals and facilitate the construction of stronger arguments for decisions about healthcare policy.

Chapter 1: Introduction

While the United States (U.S.) was ranked 44th in the efficiency of its healthcare system in 2014, its healthcare expenditures are currently the highest in the world [1]. The Institute of Medicine recognized $750 billion of waste in the U.S. healthcare system in 2009 [2]. One of the several causes of waste produced in healthcare includes poor care coordination, which represents more than 20% of the total expenditures in the U.S. healthcare sector [3]. Thirty-day preventable hospital readmissions have widely been acknowledged to represent evidence of lacking quality and poor coordination in the delivery of care. In the case of Medicare alone, readmissions cost around $24 billion per year [4].

As a problem of quality [5–10], readmissions have been addressed by the Hospital Readmission Reduction Program (HRRP). Conceived in 2013, this program established economic penalties for hospitals that experience higher readmissions than what was expected (42 CFR 412.152-154). This punishment influences the total reimbursement that hospitals receive for providing inpatient care to Medicare-covered patients.

Several concerns from the scientific community about the impact and appropriateness of the readmissions penalty policy have been raised in recent literature [11–13]. The HRRP appears to affect teaching and safety net hospitals more profoundly than those that serve affluent populations [14, 15]. Furthermore, it is not clear if readmissions are caused by hospital characteristics, patient characteristics, or both[16–18]. The results, from three years post HRRP analyses, show that the policy's objective has yet to be accomplished. In other words, readmission rates have not been consistently reduced [19], and only small reductions have been noted in the hospitals of three states[20]. Additionally, it is unclear if economic punishment can translate into meaningful (if any) improvements in the quality of care that the affected hospitals provide [21].

Engineering approaches to the solution of healthcare problems have become more common in recent years. Specifically, the application of quality improvement approaches, such as Lean and Six Sigma, have been recognized to be strategies for improving the quality and reducing the cost of care [22–25].

The work presented in this dissertation introduces a decision-based support system for hospitals, which they can be used to more effectively design policies on the implementation of disease-specific interventions based on the relative risk of readmission.

The research objective will be addressed through three specific efforts:

- The exploration of disease-specific interventions to best reduce Medicare preventable hospital readmissions.
- The development of a better prediction model for preventable hospital readmissions.
- The development of a decision-based system that allows hospital administrators to support the application of interventions that can reduce preventable hospital readmissions.

Disease-specific interventions are intended to reduce readmissions and improve the quality of care. For Medicare patients, heart failure (HF) is the disease with the greatest readmissions rate [26]. Most of the literature reviews and meta-analyses that have presented the results of interventions on hospital readmission rates have reported positive effects in HF patients. In several cases, these reviews and analyses have also reported more savings than standard-care treatment strategies for patients with HF [27–30]. A summary literature review on the impact of interventions on readmissions for HF patients, and a simulation of a scenario where an intervention is applied to all heart failure patients nation-wide, is presented and introduced in chapter 2 and more fully discussed in appendix C.

Several studies have reported models for predicting readmissions that are better [31–33] to those used in the HRRP [34–36]. In 2011, Kansagara et al. reviewed existing models that had been used to predict potential readmissions while also identifying the most commonly used variables [37]. However, these efforts were overly generalized and thus inapplicable to specific conditions. Rico et. al in 2015 studied seven years of administrative patient-level data from a network of eight hospitals in Florida, finding that higher risk of readmissions was associated to factors such as longer length of stay and patient's primary language being other than English [38]. Recent literature has reported that the best classification models are random decision forests [39]. However, when Kulkarni et al. attempted this algorithm, their c-statistics were no better than other published models [40]. A work that builds and compares a variety of methods in the search for the best machine-learning predictive model for readmissions is introduced in chapter 4 and fully presented in appendix D.

After it was established that disease-specific interventions have the potential to reduce readmissions, a predictive model was selected to assess patient's risk of readmissions. This is incorporated into a system which can provide the most accurate information to policy makers and support stakeholders in their ability to make effective healthcare policy decisions. This model is presented in chapter 5.

1.1 Research Contributions

The work presented in this dissertation makes the following contributions:

1. A review of literature on disease-specific interventions and their effect on reducing HF patient readmissions.

2. The results of a simulated scenario where an intervention that had been estimated in existing literature based data was implemented to all hospitals that served Medicare patients.

3. The development and comparison of machine learning models that predict patients' readmission risks.

4. A decision-based support system based on a mathematical optimization model, which uses disease-specific interventions and predicted readmission risks to help hospital administrators design intervention allocation policies that decrease readmissions.

The results of the proposed work will help hospital administrators to better plan in the implementation of interventions that can reduce readmissions. The proposed model is expected to enhance the impact of economic research, improve the quality of evidence resulting from the implementation of alternative policies, and increase the speed of legislative responses to these issues. Better information and a faster legislative response can positively impact the safety, quality, effectiveness, and affordability of healthcare in the U.S..

We expect that this research may facilitate the design of better policies that will directly enhance hospital care by improving safety and quality and indirectly enhance hospital care by improving efficiency and effectiveness. Finally, the achieved model could be modified to address undesirable outcomes and certain specific conditions, which could result in the design of better policies in other relevant contexts.

Chapter 2: Alternate Approach to HRRP in the Fight Against Medicare Preventable Hospital Readmissions

This paper presents a literature review that focuses on the potential for disease-specific interventions to reduce hospital readmissions. Also presented are the results from a simulated scenario where an intervention for patients with HF is applied to all patients across every hospital that provides services to Medicare patients. A complete presentation of the article "Interventions as an Alternative to Penalties in Preventable Readmissions" (published in the Journal of Hospital Administration) can be found in appendix C.

2.1 Abstract

While expenditures in healthcare in the United States are the highest in the world, it is widely known that those resources are not being used efficiently. The government addressed this situation in the Patient Protection and Affordable Care Act, in an attempt to improve quality and affordability of healthcare. In the fiscal year 2013, the Centers for Medicare and Medicaid Services began imposing financial penalties through the Inpatient Prospective Payment System to hospitals that have higher than expected readmission rates for specific diseases. The nature and effects of this new policy have raised several concerns. This article discusses Medicare's hospital readmissions reduction program and presents an alternate policy based on disease- specific interventions to reduce preventable readmissions. Our results show that a policy based on implementing disease-

specific interventions, instead of penalties, may save 33.43% of hospitals from being under the penalization level in the first year, while at the same time improving the delivery of care.

Chapter 3: Improving the Prediction of Preventable Hospital Readmissions

This chapter describes the development and comparison of statistical models that are based on machine-learning algorithms and that have been designed to improve predictions of patient readmission risks. The complete presentation of the article "Comparison of Machine Learning Algorithms for the Prediction of Preventable Hospital Readmissions" (accepted for publication in the Journal for Healthcare Quality) can be found in appendix D.

3.1 Abstract

A diverse universe of statistical models in the literature aim to help hospitals understand the risk factors of their preventable readmissions. However, these models are usually not necessarily applicable in other contexts, fail to achieve good discriminatory power, or cannot be compared with other models. We built and compared predictive models based on machine learning algorithms for 30-day preventable hospital readmissions of Medicare patients. This work used the same inclusion/exclusion criteria for diseases used by the Centers for Medicare & Medicaid Services. In addition, risk stratification techniques were implemented to study covariate behavior on each risk strata. The new models resulted in improved performance measured by the area under the receiver operating characteristic curve. Finally, factors such as higher length of stay (LOS), disease severity index, being discharged to a hospital, and primary language other than English were associated with increased risk to be readmitted within 30 days. In the future, better predictive models for 30-day preventable hospital readmissions can point to the development of systems that identify

patients at high risk and lead to the implementation of interventions (e.g. discharge planning, follow-up) to those patients, providing consistent improvement in the quality and efficiency of the healthcare system.

Chapter 4: Decision Support System for Hospitals in the Implementation of Disease-Specific Interventions to Reduce Preventable Hospital Readmissions

4.1 Introduction

The U.S. healthcare system is the most expensive healthcare system in the world and one of the least efficient in the delivery of care. In 2012, Berwick and Hackbarth [3] identified care coordination as a reason for inefficient use of resources. Preventable hospital readmissions are widely recognized as an indicator of poor quality of care and care coordination [8, 9]. In 2009, Jencks and Coleman [4] estimated that 19.6% of patients experienced preventable readmissions for years 2003 and 2004. In addition, the Agency for Healthcare Research and Quality reported a cost of $41.3 billion for all-cause hospital readmissions in 2011 [26].

In 2013, the Centers for Medicare and Medicaid Services started the HRRP, intended to reduce payments by up to 3% for hospitals with excessive readmissions. The conditions monitored by that program included HF, pneumonia (PN), and acute myocardial infarction (AMI). In the following years, additional conditions, such as total hip arthroplasty (THA), chronic obstructive pulmonary disease (COPD), total knee arthroplasty (TKA) in 2014, coronary artery bypass grafting (CABG) in 2015, and aspiration PN and sepsis (not severe) with PN in 2016, were added to that list.

The research community has placed special attention on the problem of preventable hospital readmissions. Kansagara et al.'s 2011 report of several models that had been used to predict readmission risk, they concluded that a logistic-regression-based model was the best solution to reducing readmissions [37]. Following this approach, Rico et al.'s 2015 study used logistic regression models to inspect the significance of variables and compared them with results that had been derived from proportional hazard models. Their findings revealed that higher risk of readmissions is associated with factors such as longer LOS and patient's primary language being other than English [41]. In 2015, Kulkarni et al. determined that neural networks outperformed decision trees and logistic regression models during predictions of readmissions at various hospitals [40]. In addition, Garcia-Arce and Zayas-Castro's 2017 comparison of four different machine-learning algorithms asserted that neural networks outperformed other types of models [42].

A considerable amount of research has documented the design, implementation, and results of intervention trials that have been designed to reduce readmissions [43]. Results have shown that interventions can both reduce readmissions and create savings during treatment of patients with HF [19]. For example, in Naylor's implementation of a transitional care model that paired nurses to older adults, and which monitored patients from their admission until 90 days after they were discharged, the reported differences between the intervention and control groups were 36% for readmitted patients and 39% for costs [44].

The aim of this work is to enable hospital administrators to make data-driven decisions during the allocation of interventions that can reduce readmissions. Our approach combines two elements: predictive models that can identify the risk for readmissions and the notion that certain disease-specific interventions can reduce readmissions while creating savings. The result is a decision support system based on a mixed-integer optimization model designed to provide hospital administrators with a system capable to assist in data-driven decisions on intervention policies.

Many problems in healthcare have been successfully addressed through the implementation of operation research approaches, wherein the main areas of application include practice, planning, logistics, management, and preventive care [45, 46]. Recent literature has reported that mixed-integer programming approaches support decisions that are related to staffing [49–51], organ donations [52], blood donations [53], vaccine distributions [54], operation room schedules [47, 48], and home healthcare planning [55, 56] .

Clinical decision support systems can be classified by models or treatment algorithms, questionnaires or computer-based tools, and classification systems or clinical prediction rules [57]. While diagnoses have still not been effectively addressed by clinical decision support systems [58], researchers have recognized the value in using classification tools to help physicians identify patients who are at risk for adverse outcomes, and therefore, the importance of allocating interventions that are designed to reduce the risk for those outcomes to occur [59].

4.2 Methods

By leveraging the potential of clinical decision support systems (machine-learning algorithms for classification) and tactical-operational decision support systems (mixed-integer programming), this work aims to address the issue of preventable hospital readmissions and to create an integrated decision support system that can enable hospital administrators to make tactical-operational decisions as they allocate interventions to patients who are at risk for readmission. We call this model the Readmissions Risk Targeted Interventions (RRTI) model.

The first element in the RRTI model is an estimation of intervention costs and intervention effectiveness. Final implementation of the RRTI model will require hospital-specific data to define more realistic estimates of these values. To create this model, we will consider the values that were estimated in appendix C for a sample intervention. These values were extracted from a literature review of studies that documented interventions that had been designed to reduce the risk of readmissions in HF patients. As an expansion of the work presented in appendix C, hospital administrators will be given the ability to decide whether to implement interventions to reduce readmissions and to avoid future penalties based on their actual readmission rates and potential penalties. Secondly, a statistical classification model will be made available to hospital administrators that wish to further decrease the cost of implementing interventions. This can be achieved by narrowing the number of patients that are allocated interventions and by using the classification model to stratify patients based on their risks for readmission. During the decision process, the cost of implementing the statistical model will also be considered. Figure 4.1 depicts a global view of the system. In summation, the RRTI model will assist hospital administrators in the development of policies by teaching them how to implement interventions based on their actual readmission risks and mix of patients.

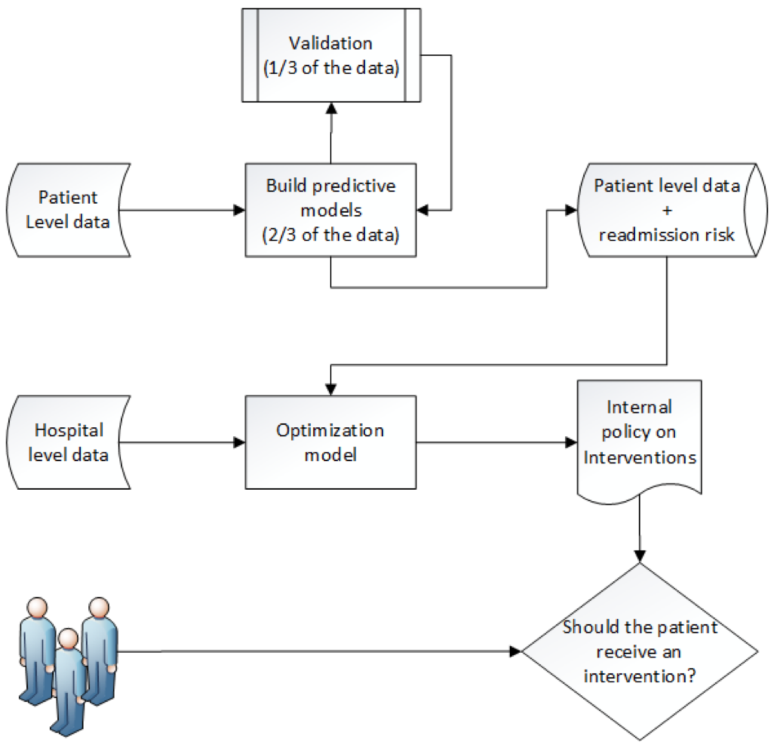

Figure 4.1: RRTI diagram.

To combine the concepts about of the number of intervened patients and the usage of a predictive model, we considered another decision, in which a hospital may use a cost-effective predictive model to pursue further reductions in readmissions. In cases where no information about patient readmission risks are available, administrators can choose to allocate interventions to every patient for whom they provide care (in this case, patients with HF). However, as the classification model helps more information about patients' readmission risks to become available, the pool of patients who receive interventions can become smaller. In the RRTI model, while the parameter $\alpha_{j,k}$ is used to estimate the effectiveness of readmissions when the maximum number of patients has been allocated interventions, the parameter $\alpha^{f}_{j,k}$ is the modified effectiveness when a smaller pool of patients has been allocated interventions. The parameter $\theta^{f}_{j,k}$ is used to account for a decrease in the number of patients who have been allocated interventions after a hospital's administrator has used a predictive model. The unknown parameters $\theta^{f}_{j,k}$ and $\alpha^{f}_{j,k}$ are primarily set to an arbitrary value and are later inspected for sensitivity.

Objective function:

$$Min \sum_{j \in J}\left[\sum_{k \in K}\left[IC_{ijk} * D_{ijk}\right]\right] + \sum_{j \in J}\left[\sum_{k \in K}\left[smc_i * f_{ij}\right]\right] - \sum_{j \in J}\left[DRGp_{ij}NOP_{i,j_i}\left[\sum_{k \in K} D_{ijk}\left(\left(1-e_{ij}\right)\frac{\alpha_{jk}}{3}\right)\left(1+\alpha^{f}_{jk}f_{ij}\right)\right]\right]$$

Subject to the following restrictions:

(1) $\sum_{j \in J}\sum_{k \in K} D_{ijk}\ IC_{ijk} + f_{ij}\ smc_{ij} \leq \sum_{j \in J} DRGtp_i(1-PR_i) \quad \forall i$

(2) $D_{ijk} \leq e_{ij} \quad \forall\, i,j,k$

(3) $\sum_{k \in K} D_{ijk} \leq 1 \quad \forall\, i,j$

(4) $IC_{ijk} - \left(\left(\frac{NOP_{ij}}{3}\right)c_{jk}\right) \cdot \left(1 - f_{ij}\theta^{f}_{jk}\right) \geq 0 \quad \forall\, i,j,k$

(5) $f_{ij} \leq \sum_{k \in K} D_{ijk} \quad \forall\, i,j$

$D_{ijk} \in \{0,1\} \quad \forall\, i,j,k$

$f_{ij} \in \{0,1\} \quad \forall\, i,j$

Figure 4.2: RRTI optimization model.

The RRTI model is presented in figure 4.2. Its objective function is designed to minimize total cost. We define total cost as the addition of three different types of costs: the intervention cost, the cost of implementing the statistical method, and the savings obtained in the reduction of penalties that result due to intervention allocation, use of the predictive model, or both. The cost of allocating interventions is estimated from the results in appendix C. Because fewer patients are allocated interventions once the predictive model has been used, this cost should be reduced. The savings introduced by intervention and the use of the predictive model are modified with the parameter $\alpha_{j,k}$ for the intervention and with the parameter $\alpha^{f}_{j,k}$ for the intervention and predictive model. The cost of implementing the predictive model can be understood as the time nurses spend reading the output and the investment in its application to a hospital's technical systems (IT, analysts, etc.).

Restriction (1) ensures that the cost of the action (interventions allocated and/or use of a statistical model) does not offset the cost of the penalty. This restriction will include the idea that interventions need to be cost effective. Restriction (2) guarantees that if a disease does not present excessive readmission risk, then the RRTI model will not recommend the allocation of interventions (an excess greater than one means that there are more readmissions in a hospital than is expected for its risk group). Restriction (3) establishes the number of implemented interventions to one per disease and hospital. Restriction (4) assures the reduced cost of interventions when there is a predictive model in place. Finally, restriction (5) ensures that predictive models will only be enacted when an intervention has been recommended.

The model was implemented in the General Algebraic Modeling System (GAMS) and solved using the Discreet Continuous Optimizer (DICOPT) solver. The data used to run the model corresponds with data that have been collected from hospitals that participated in Medicare's IPPS. The IPPS bundles payments for admissions according to conditions that have been categorized into a diagnosis-related group (DRG). Every year, CMS releases a policy known as the final rule, which contains aggregated data that have been collected from hospitals and lists of adjustment factors, excess readmissions, and other variables used in the calculation of claim reimbursements. The IPPS final rule for the fiscal year of 2017 was used in the model. The model's output includes a set of decisions about whether a hospital should allocate interventions, the number of patients who should be allocated interventions, and if investment in a predictive model that targets high-risk patients should be implemented.

4.3 Results

To provide a global perspective on the decisions that have gone into the RRTI model, the hospitals that had been penalized due to excess readmissions for patients with HF were analyzed. Figure 4.3 shows all hospitals that received penalties (with an adjustment factor less than 1) and that had excessive readmissions for patients with HF (with excess readmissions for HF that were greater than 1). Data were obtained from the publicly available IPPS final rule for the fiscal year of 2017. From the 3,448 hospitals that were initially considered, 1,403 hospitals met this inclusion criteria.

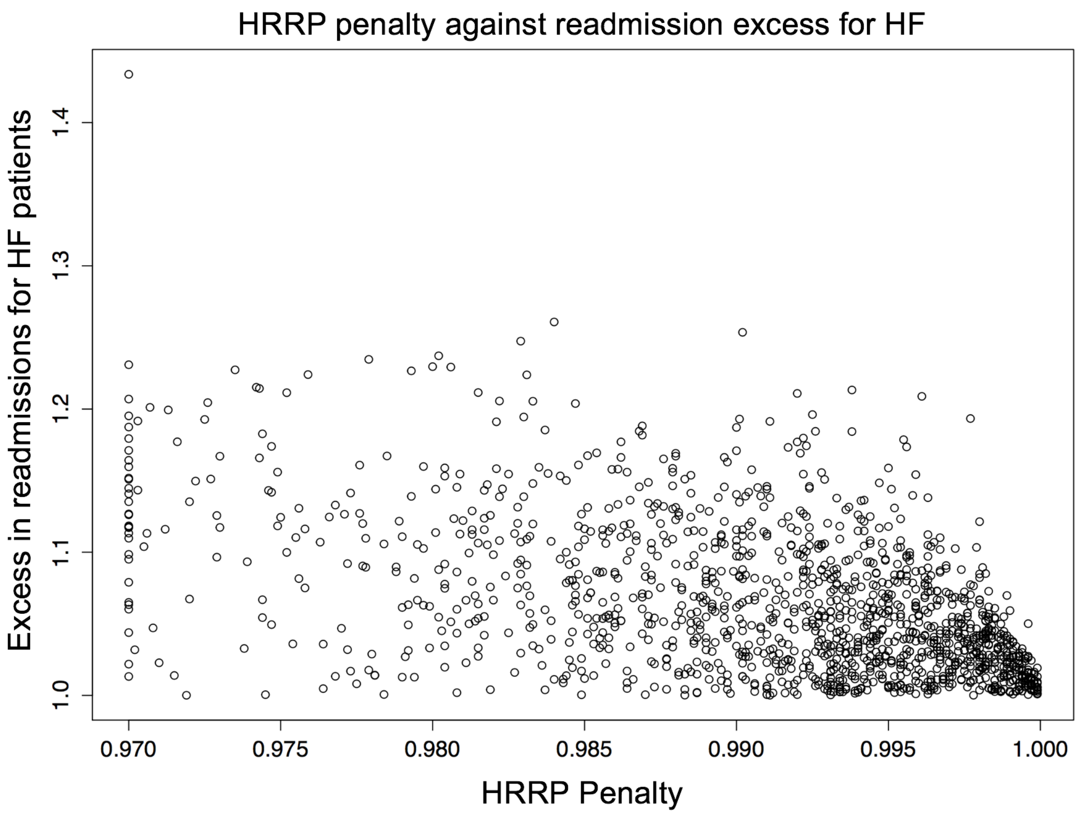

Figure 4.3: Readmissions excess.

The 1,403 hospitals were segregated into classes to provide representative cases of the RRTI model. We created nine artificial clusters of patients (see figure 4.4), and clusters were created based on the following three segmented categories of readmission for patients with HF: low level of excess (greater than 1 and less than 1.1), medium level of excess (greater than 1.1 and less than 1.2), and high level of excess (greater than 1.2). The following three segmented categories for penalties were also considered: low penalty (greater than 0% and less than 1%), medium penalty (greater than 1% and less than 2%), and high penalty (greater than 2%).

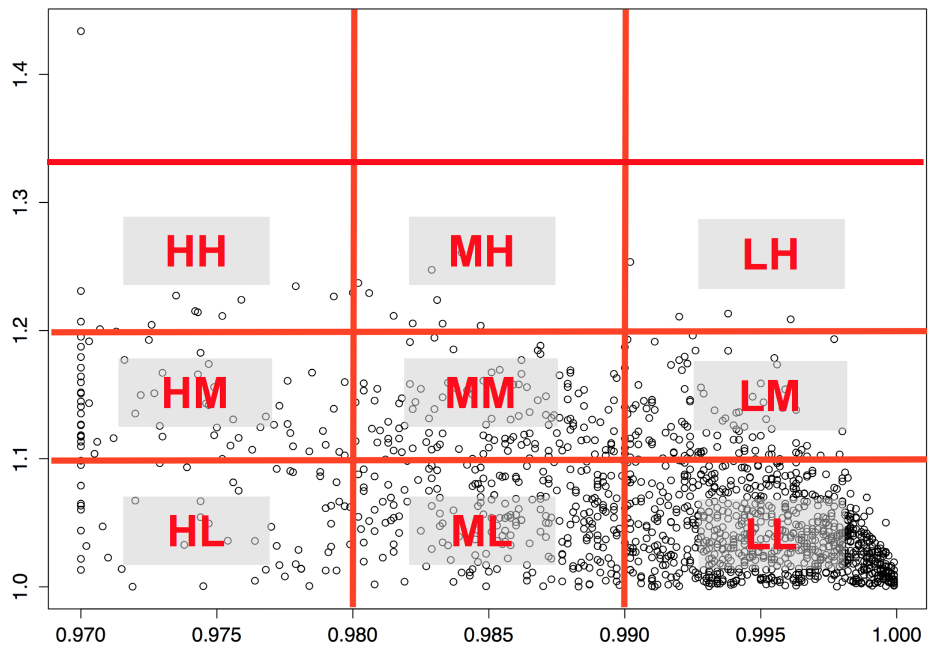

Figure 4.4: Sample hospitals used for preliminary results of the model.

From the nine categories (all combinations of the six categories), nine hospitals were selected (table 4.1). When possible, hospitals were selected when they shared similar characteristics, which was not always possible since most critical hospitals (those in the categories in the upper left of figure 4.4) had fewer cases than the others. To completely illustrate the status of every one of the studied hospitals, each hospital's state and number of licensed beds is provided (as reported in public data made available by the American Hospital Directory).

Table 4.2 shows the considered hospitals' primary characteristics. The wage index factor (WIF) is an adjustment that accounts for the geographical and socioeconomic differences of hospitals

Table 4.1: Sample hospitals.

	Hospital	State	Lic. Beds
HL	Glenwood Regional Medical Center	LA	275
HM	Saint John's Riverside Hospital - Andrus Pavilion	NY	378
HH	Piedmont Henry Hospital	GA	277
ML	Medical Center of Trinity	FL	288
MM	NYC Health + Hospitals Coney Island	NY	371
MH	Mount Sinai Beth Israel Medical Center	NY	934
LL	SSM Health DePaul Hospital- Saint Louis	MO	474
LM	MountainView Hospital	NV	336
LH	NYC Health + Hospitals Kings County	NY	634

that have participated in Medicare's IPPS. A higher WIF is directly proportional to higher costs in penalties and a higher monetary amount for claims. A penalty is the amount taken from a penalized hospital's annual reimbursements. This penalty has an upper bound of 3%. Therefore, hospitals with an exact upper bound of 3% were avoided, as their excesses could be much worse than what we would be able to infer from the available data. The HF excess is the excess of readmissions for patients with HF in the chosen hospitals, and HF cases are the number of cases that were used in the calculations. The number of cases were compiled over a three-year period. This means that roughly a third of the cases from each of the three years that were observed for our calculations. This can be safely assumed once we have checked the previous year's changes in the inclusion/exclusion criteria for diseases. This consideration is particularly important for PN since the inclusion criteria for the fiscal year of 2017 was expanded to include PN and sepsis (not severe) and aspiration PN.

To form a complete illustration of the samples, tables 4.3 and 4.4 describe the excess of readmissions for all diseases and the number of cases considered for all diseases in the sample hospitals. It should be noted that some of the diseases listed in table 4.3 show no excess readmissions. A lack of excess readmission occurs when a hospital has less than 25 cases and is therefore not required to report them. Also, diseases with excess readmissions of less than 1 are not included in the

Table 4.2: Specific parameters from sample hospitals.

	WIF	Penalty	HF Excess	HF Cases
HL	0.7675	2.12%	1.0897	785
HM	1.3505	2.57%	1.1658	656
HH	0.9222	2.65%	1.2273	575
ML	0.8994	1.15%	1.0569	456
MM	1.2936	1.58%	1.1533	470
MH	1.3505	1.71%	1.2474	1009
LL	0.8987	0.39%	1.0399	610
LM	1.1825	0.95%	1.1576	609
LH	1.2936	0.98%	1.2536	152

calculations for the penalty (adjustment factor). Further detail on how the adjustment factor is calculated can be found in appendix C.

Table 4.3: Readmissions excess in sample hospitals.

	AMI	HF	PN	TKA/TH	COPD	CABG
HL	1.1749	1.0897	1.0995	0.8679	1.0193	1.1778
HM	1.0226	1.1658	1.2723	0.9821	1.1884	0.0000
HH	0.9772	1.2273	1.1519	1.1848	0.9811	0.0000
ML	1.0038	1.0569	1.0859	1.1543	0.9776	0.0000
MM	1.1260	1.1533	1.1582	0.0000	1.0440	0.0000
MH	1.1118	1.2474	1.1588	0.9163	1.1703	1.0174
LL	0.9934	1.0399	1.0811	0.9368	1.0025	0.9564
LM	1.0481	1.1576	1.0927	0.8529	1.0264	0.9044
LH	1.0004	1.2536	1.1569	0.0000	1.0981	0.0000

Table 4.4 reveals that hospital MH presented more patients than the other hospitals in the sample. This can be explained by its larger size when compared to the other hospitals.

The cost of intervention, which was estimated in appendix C, was set to \$36.6 per patient. The effectiveness was set to 33%. The cost of the predictive model's implementation was set to

Table 4.4: Number of cases in sample hospitals.

	AMI	HF	PN	TKA/THA	COPD	CABG
HL	459	785	835	59	481	106
HM	93	656	555	126	518	0
HH	130	575	510	490	439	0
ML	252	456	457	370	540	12
MM	58	470	458	2	238	0
MH	535	1009	1530	498	842	88
LL	291	610	651	1130	345	47
LM	323	609	873	223	619	125
LH	29	152	112	5	99	0

$34,000 to cover around 0.3 of an IT analyst's salary for 6 months (time we estimate it would take to adapt and implement the model to a hospital's technical system). The increased effectiveness in the reduction of interventions during implementation of the predictive model was initially set to 40%, and the savings in intervention costs due to use of the model was initially set to 20%. The values for the last two parameters were set arbitrarily, and therefore, sensitivity analysis will be performed.

The results of the implemented model are presented in figure 4.5. The results are expressed as (D, F), where D is 1 if a hospital implemented an intervention, or otherwise 0, and F is 1 if a hospital implemented the predictive model, or otherwise 0. The results in figure 4.5 show that all hospitals implemented interventions. This was expected due to our methods for selecting the considered hospitals (penalized hospitals with excessive readmissions for HF patients). It is worth noting that HM and MH were the only hospitals to implement a predictive model. For MH, this was due to a mixture of high WIF, a large number of HF cases (the largest in the sample), and a severe excess of readmissions for patients with HF. On the other hand, HM's use of a predictive model can be explained by its combination of a high WIF and higher penalty than that of the other hospitals.

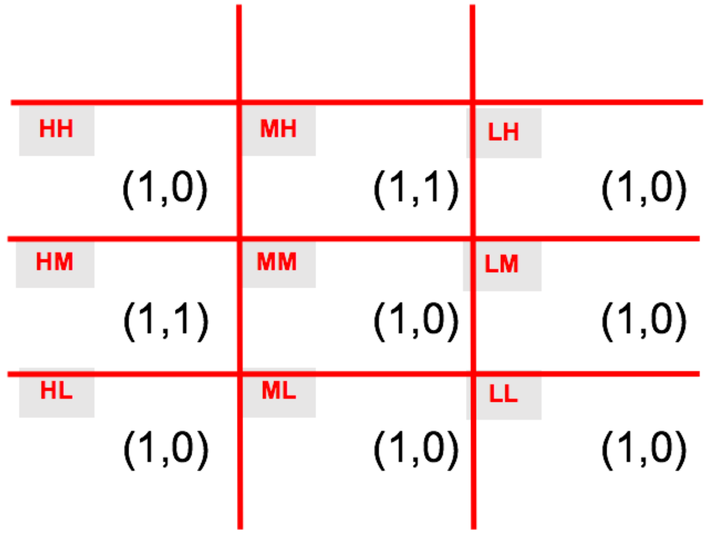

Figure 4.5: RRTI results.

To study the effect of the unknown parameters in the model, a brief sensitivity analysis was conducted. The aim of the analysis was to explore how hospital administrators modified their decisions when there were improvements to savings and the effectiveness of care due to reduced penalties and intervention costs as a result of the predictive model's implementation.

Table 4.5 shows the results of the decisions that hospital administrators using the RRTI model made when savings accrued due to the implementation of a change to the predictive model. To test the effect of θ in the results, two new instances were created with θ=0.1 and θ=0.6. The results revealed that regardless of the value of θ, the administrators at HM and MH still decided to implement the predictive model. Additionally, HH's administration decided to implement the predictive model after their savings increased from 20% to 60%. By contrast, the administrators at HL, ML, MM, LL, LM, and LH did not use the predictive model after the application of either scenario.

Table 4.6 shows the results of the decisions that hospital administrators using the RRTI model made when a reduction of readmissions occurred due to the implementation of a change to the pre-

Table 4.5: Sensitivity over savings of predictive model.

theta	0.1		theta	0.2		theta	0.6	
alpha_F	0.4		alpha_F	0.4		alpha_F	0.4	
alpha_D	0.33		alpha_D	0.33		alpha_D	0.33	
	D	F		D	F		D	F
HL	1	0	HL	1	0	HL	1	0
HM	1	1	HM	1	1	HM	1	1
HH	1	0	HH	1	0	HH	1	1
ML	1	0	ML	1	0	ML	1	0
MM	1	0	MM	1	0	MM	1	0
MH	1	1	MH	1	1	MH	1	1
LL	1	0	LL	1	0	LL	1	0
LM	1	0	LM	1	0	LM	1	0
LH	1	0	LH	1	0	LH	1	0

dictive model. To test the effect of α^f in the results, two new instances were created with α^f=0.1 and α^f=0.9. The administrators at HM and MH decided not to implement the predictive model when the reduction to readmissions was as low as 10%. On the other hand, the administrators at HL, HH, MM, and LM decided to implement the predictive model when the boost in readmission reductions was 90%. Hospitals ML, LL, and LH did not implement the predictive model in spite of the multiple variations to the reduction in readmissions. In tables 4.5 and 4.6, it is worth noting that hospitals ML, LL, and LH did not implement the predictive model in spite of improved savings and reductions to readmissions.

Table 4.6: Sensitivity over reductions in readmissions from predictive model usage.

theta	0.2		theta	0.2		theta	0.2	
alpha_F	0.1		alpha_F	0.4		alpha_F	0.9	
alpha_D	0.33		alpha_D	0.33		alpha_D	0.33	
	D	F		D	F		D	F
HL	1	0	HL	1	0	HL	1	1
HM	1	0	HM	1	1	HM	1	1
HH	1	0	HH	1	0	HH	1	1
ML	1	0	ML	1	0	ML	1	0
MM	1	0	MM	1	0	MM	1	1
MH	1	0	MH	1	1	MH	1	1
LL	1	0	LL	1	0	LL	1	0
LM	1	0	LM	1	0	LM	1	1
LH	1	0	LH	1	0	LH	1	0

While the first three rows in table 4.7 show the specific parameters for hospitals ML, LL, and LH and compare the weighted averages for other diseases in the same hospitals, the last row shows the same values for HM, which was one of the responsive hospitals. It should be noted that while the unresponsive hospitals that were compared had only one critical value (marked with red), HM had four critical values. As a result, we can conclude that hospitals that perform poorly are more likely to use a statistical model to pursue savings and further reductions in readmissions.

Table 4.7: Comparison on unresponsive hospitals.

	Excess HF	Weighted average	NOP	ave NOP	WIF	Adj. Factor
ML	1.0569256	1.080300728	456	383.75	0.8994	1.15%
LL	1.0399383	1.048588314	610	535.33333	0.8987	0.39%
LH	1.2535552	1.167948142	152	98	1.2936	0.98%
HM	1.1658324	1.197379519	656	455.5	1.3505	2.57%

4.4 Discussion and Conclusions

Preventable hospital readmissions are considered to represent waste, a lack of care coordination, and poor quality in the delivery of care. In recent years, hospitals that have presented excessive readmissions have received penalties to their annual reimbursements by CMS. This has led to certain disparities, as these penalties have affected safety net hospitals and hospitals that provide care for complex cases.

The work presented in this chapter aims to combine the following two ideas: that interventions can create savings and reduce readmissions and that every patient's risk for readmission can be estimated with relative confidence. These two ideas have been combined in an optimization model that allows hospital administrators to make data-driven decisions as they implement interventions and to explore if a predictive model of readmission risk can boost reductions in penalties that they may have received.

From the preliminary results of the model, it can be concluded that the most critical hospitals, those with higher penalties and excessive readmissions, benefit the most from using a statistical model. In addition, while we observed hospitals that received penalties due to excessive readmissions, we also found that several of their administrators consistently chose not to implement predictive models.

The decisions each hospital administrator make about whether they should implement interventions and predictive models are very complicated, as these decisions involve several different pieces of information that may not even be available to members of a hospital's leadership. Additional research to refine and further improve the predictive model, as well as to create an interface designed to deliver results to business stakeholders, is therefore critical to advancements in the reduction of readmissions.

The work presented in this chapter carries limitations. Several estimations of data from published articles have been introduced to the RRTI. Because many of these studies observed very specific populations, their results may not apply to other institutions. Few studies have reported results from interventions that used cross-sectional data and rigorous statistical models. In addition, while the results of previous studies have been based on de-identified information that was made available by CMS, certain estimations were made to make these data usable. By gaining access to identifiable patient-level data on the claims issued from hospitals, we would be able to estimate our parameters more realistically, and therefore, provide more adjusted results.

Many new ideas could be explored in the future. For instance, this model could be improved to include more sophisticated features, such as stochastic effectiveness (instead of deterministic as it is now), variable costs for the use of the predictive model, and a flexible continuous method to model the number of patients who receive interventions. For policy makers, this model could also be redefined to include interactions between hospitals and policy makers (e.g., CMS) to test hospital responses to different instances where incentives have been directed to reduce preventable hospital readmissions.

Chapter 5: Conclusions

The U.S. healthcare system suffers due to its high expenditures and lower quality of care. Excesses in fraud, abuse, prices, bureaucracy, and overtreatment, combined with failures in execution of care and lack of coordination, make up about 20% of the country's healthcare expenditures.

High readmission rates are considered to be evidence of poor quality healthcare and a lack of care coordination. It is due to these factors that CMS levied the HRRP to impose financial penalties on hospitals with excessive readmissions. This policy attracted criticism due to its considerable impact on hospitals that care for the sickest and most vulnerable patients. It has been argued that HRRP reductions have most severely affected teaching and safety-net hospitals [60], which could be deemed inappropriate since it is known that patients who are older, present multiple comorbidities, or hold lower socioeconomic statuses are more likely to be readmitted [13].

Existing literature has provided evidence that adequate interventions can reduce preventable hospital readmissions. Interventions can be categorized as the addition of follow-ups, modifications to the discharge process, and the provision of health education to patients. In addition, it has been determined that interventions can reduce preventable hospital readmissions, and in some cases, provide savings.

The work presented in this dissertation was developed sequentially in the search for better methods to decrease readmissions and improve quality of care. The work's primary objective was to develop a decision-based support system that could aid hospital administrators in their capacity to allocate interventions to patients at risk for preventable readmissions. This objective was addressed with research from the following three studies:

1. "Interventions as an Alternative to Penalties in Preventable Readmissions."

2. "Comparison of Machine Learning Algorithms for the Prediction of Preventable Hospital Readmissions."

3. "Decision Support System for Hospitals to Allocate Interventions to Patients at Risk of Readmissions."

The first research project explored the published results of clinical trials that aimed to study the effects of disease-specific interventions on HF patients. Existing literature was difficult to compile, as many studies did not report results in a standardized way. By using data from eligible studies, an intervention was estimated, and a scenario in which this intervention could be applied to all hospitals was designed. As expected, results from the simulation yielded consistent reductions to penalties and readmissions.

This work had clear limitations. For instance, the deterministic reduction was introduced in all hospitals. By design, interventions were also applied to all hospitals regardless of their rates of readmission. Additionally, interventions were allocated to all patients, and personal differences that could influence the impact of interventions were not considered. By considering the unique characteristics of all patients, a system capable of helping hospital administrators to decide whether they should allocate intervention policies would enable and empower hospitals to reduce readmissions and improve their quality of care.

The second work focused on statistical models to understand and predict readmission risks. As opposed to several of the models that have been presented in existing literature, we used the same inclusion/exclusion criteria as CMS and sought models that were comparable with the governmental agency's most recent standards. Machine learning algorithms, such as the random forest, neural networks, support vector machine, and gradient stochastic boosting, were used to build models for HF, PN, AMI, COPD, and diabetes. Additionally, we used special techniques to inspect potential improvements that could be made to the process of addressing imbalance and feature selection from the data. The results revealed that neural networks outperformed other algorithms except in the case of HF. For HF, the gradient stochastic boosting proved to be the most effective algorithm. Furthermore, the results of the risk stratification analysis revealed that higher acuity and primary languages other than English were generally considered to be risk factors for readmission.

The final work presented the development of a decision support system that used and combined the ideas discussed in the previous two research projects to enable hospital administrators to make data-driven decisions in the implementation of interventions and design of policy for intervention allocations. A mixed-integer programming model was then proposed to assist in decisions about intervention implementation, the number of patients to be allocated interventions, and whether a statistical predictive model was required to further reduce the costs of applying interventions. Our results confirmed that a hospital would be more likely to implement a predictive model if it presented a critical situation, regardless of savings or reduced costs. We also discovered a set of hospitals that did not implement the predictive model after they had been penalized for excessive readmissions. The reasons why certain administrators chose not to implement a predictive model were not immediately clear from their data, and therefore, further research will be required to refine the model so that it can provide better insight to administrators as they make these strategic decisions.

The developed research can contribute to multiple stakeholders in the healthcare sector. Hospital administrators can use the RRTI model to design in-hospital strategic and tactical policies that can inform operational leaders on how to allocate interventions that are based on their hospitals' specific data and needs. In addition, the RRTI model can be stacked and computed for use by all hospitals that participate in Medicare. Policy makers can also use this configuration of the RRTI model to add inpatient claims data to the IPPS, which is available at CMS' Research Data Assistance Center (ResDAC). The model could also allow policy makers to conduct sensitivity analyses on various levels of incentives or enable them to include new conditions that test the reaction of other hospitals in the network to these changes.

The work presented in this dissertation has limitations. For instance, there is no clear agreement in the scientific community about who is responsible for preventable hospital readmissions. Some researchers have concluded that since many of the factors associated with readmissions are deemed unalterable, they are therefore unavoidable [61] and far from the control of hospitals or their operational leaders [62]. Others have recognized that while not all readmissions can be avoided, provisions of better care can significantly reduce readmission rates [63].

However, the HRRP model may be achieving some degree of success, as early results from New York state [20], in addition to national results from the Department of Health and Human Services, have recently revealed decreased rates in readmission [64]. All the same, as reductions in readmissions for non-documented approaches make it difficult to measure the effectiveness of new interventions, additional studies may be required.

As a practical limitation, we used limited public data to estimate most of the parameters and based assumptions from the first and last part of the dissertation. These estimates could become more realistic as patient-level data are made available. In conclusion, the results of this work have led us to propose the following question: does the reduction of preventable hospital readmissions actually help to increase quality and reduce unnecessary costs? As a starting point, previous efforts to decrease patients' lengths of stay have had no reported effect on increases to readmissions levels [65, 66]. Because readmission rates are decreasing, and thus, the HRRP model may be achieving some degree of success, the answer to this question remains elusive [64], and more studies that aim to answer this question should be developed. Regardless, the studies reported in this work prove that the implementation of interventions can help hospitals to create savings, decrease readmission risks, reduce excessive readmission rates, and improve quality in the delivery of care.

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Appendices

Appendix A: General lnformation About Appendices

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>
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> Doctoral Candidate
> University of South Florida
> Industrial & Management Systems Engineering
>
> **Website**: www.linkedin.com/in/garciampu/en
> **Phone: +1** 813 898 7730
> **+56** 45 2 947116

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Edith Lecea,
Editorial Assistant
Journal of Hospital Administration, Sciedu Press

1120 Finch Avenue West, Suite 701-309, Toronto, ON., M3J3H7, Canada
Tel: 1-416-479-0028 ext. 213
Fax: 1-416-642-8548
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Appendix C: Interventions as an Alternative to Penalties in Preventable Readmissions

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ORIGINAL ARTICLE

Interventions as an alternative to penalties in preventable readmissions

Andres Garcia-Arce [*], Jose L. Zayas-Castro

College of Engineering, University of South Florida, Tampa, FL, USA

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ABSTRACT

While expenditures in healthcare in the United States are the highest in the world, it is widely known that those resources are not being used efficiently. The government addressed this situation in the Patient Protection and Affordable Care Act, in an attempt to improve quality and affordability of healthcare. In the fiscal year 2013, the Centers for Medicare and Medicaid Services began imposing financial penalties through the Inpatient Prospective Payment System to hospitals that have higher than expected readmission rates for specific diseases. The nature and effects of this new policy have raised several concerns. This article discusses Medicare's hospital readmissions reduction program and presents an alternate policy based on disease-specific interventions to reduce preventable readmissions. Our results show that a policy based on implementing disease-specific interventions, instead of penalties, may save 33.43% of hospitals from being under the penalization level in the first year, while at the same time improving the delivery of care.

Key Words: Disease-specific interventions, Readmissions, Medicare

1. INTRODUCTION

Over the last four years, the United States (US) spent on average 17.74% of its gross domestic product (GDP) on healthcare, the highest in the world. This is more than twice the rate of other high-income countries which was 7.78%.[1] However, this high expenditure has not translated into a better quality. To illustrate, in 2001 the performance of the US healthcare system was ranked 37^{th} and in 2014 it was classified 46^{th} in efficiency.[2,3] Furthermore, in 2012 the Institute of Medicine estimated that 30% of the total expenditures in 2009 on healthcare were wasted.[4] In summary, the US healthcare system continues to face significant challenges in performance, quality and cost.

It has been argued that preventable readmissions are evidence of the deficiency in the quality of care,[5,6] generating potential harm to patients and unnecessary costs.[7] Much and varied research has been done to identify the causes of readmissions, their validity, and their interaction when predicting the risk of readmissions.[8,9] Furthermore, preventable readmissions affect the Medicare-covered population. In fact, Jencks *et al.* in 2009 estimated that between 2003 and 2004, 19.6% of patients were unexpectedly readmitted, representing in 2004 a cost of $17.4 billion.[10] The Robert Wood Johnson Foundation in 2013 estimated that readmissions represent $26 billion for Medicare, of which $17 billion is estimated as the cost of avoidable readmissions.[11]

[*]**Correspondence:** Andres Garcia-Arce; Email: andresg@mail.usf.edu; Address: College of Engineering, University of South Florida, 4202 E. Fowler Avenue, ENB118, Tampa, FL 33620, USA.

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The US began a reform process promising a better, and less costly, healthcare system.[12] The Patient Protection and Affordable Care Act (ACA) established that payments to eligible hospitals will be adjusted as an incentive to reduce readmissions. Therefore, the Centers for Medicare and Medicaid Services (CMS) started the hospital readmission reduction program (HRRP) which includes a set of economic penalties through the inpatient prospective payment system (IPPS) to hospitals that show excessive readmissions in certain diseases. However, imposing financial penalties to incentivize hospitals in reducing preventable readmissions has raised concerns such as the appropriateness of the policy or the possible undesired effects to hospitals.

This study explores the feasibility and preliminary effects of a disease-specific intervention as an alternative to HRRP. The goal is to decrease readmissions and reduce cost while directly improving the quality of care.

First, a review of literature is done to prove the plausibility of the assumption that interventions reduce the amount of preventable readmissions. Secondly, a different review is conducted to describe the available results of interventions in one specific disease. Then, using the data available from CMS, a simulated case is proposed and results from it are calculated. Finally, the simulation results are studied and compared with the available results from the current HRRP policy.

2. Background

2.1 Inpatient prospective payment system

The IPPS, introduced in section 1886 (d) of the Social Security Act, is used by Medicare to reimburse hospitals for inpatient care services provided to covered patients. In the IPPS, the reimbursement calculation depends mainly on the diagnosis of the admission (not procedures), represented by the diagnosis related group (DRG) weight. The calculation of this payment is shown in Equation 1.

$$DRG_{weight}(i,j) = (Labor \times WIF(j) + Non\,Labor) \times DRG_{weight}(i), \forall i \in I, \forall j \in J \quad (1)$$

Where *I* and *J* represent the set of providers and hospitals considered in IPPS, respectively. $DRG_{weight}(i)$ is a weight that accounts for the differences among the *i* diseases in terms of resources and procedures. The*WIF(j)* term accounts for the socioeconomical differences in each geographic location, and the labor and non-labor wage relates to the different portions of expenses related to the medical service provided. Medicare also adjusts for factors such as longer stays, disproportionate care hospital, indirect medical education, etc. The payment before adjustment is referred here as DRG base payment ($DRG_{base}(i,j), \forall i \in I, \forall j \in J$).

2.2 Calculations for the excess of readmissions

The next element considered in the HRRP is excess of readmissions for the following conditions: acute myocardial infarction (AMI), heart failure (HF) and pneumonia (PN). The excess is calculated using patient-level administrative data for three years. The application of HRRP for FY2013 uses data from FY2009, FY2010 and FY2011. A hierarchical logistic regression is implemented to account for the average effect among hospitals, offering a risk adjustment approach. The expected readmissions measure, the denominator, is obtained by regressing the specific patient-level data using the average intercept while the numerator is obtained using the average intercept and the specific "residual" for each hospital (42 C.F.R. §412.150 - §412.154).

2.3 Hospital readmission reduction program (HRRP)

In the IPPS final rule for FY2013, an adjustment factor (AF) is applied to all reimbursements billed to Medicare from hospitals that present an excess of readmissions for AMI, HF and PN.[13] In FY2015, total knee arthroplasty (TKA), total hip arthroplasty (THA) and congestive obstructive pulmonary disease (COPD) are included in the calculations of the HRRP. The AF depends on the DRG base payment for each specific disease (AMI, HF and PN in FY2013), the number of cases in the period considered, the payments for all admissions made in the period and the excess of readmissions for AMI, HF and PN (see Equation 2).

This AF affects the total payment for all admissions billed to Medicare through IPPS during the fiscal year. The implementation of the AF considers a ceiling adjustment of 1% for FY2013, which was raised to 2% by FY2014 and 3% for FY2015 (w/o quotations).

From the beginning the methodology, effects and results of HRRP policy attracted criticism. Some of the concerns relate to the inappropriateness of the nature of the incentive,[14] the impact on the most vulnerable hospitals[15] or the adjustments of payments applied to all diseases based on a small portion of them.[16] Also, it is unclear whether the reduction in the payments to hospitals will improve the quality of care.

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$$Adj.Factor(j) = 1 - \frac{\sum_{i \in I} \{[Excess(i,j) - 1] \times DRG_{base}(i,j) \times NOC(i,j)\}}{DRG_{all\,admissions}(j)}, \forall j \in J \quad (2)$$

Where *Adj.Factor(j)* represents the final adjustment applied to reimbursements, *Excess(i, j)* is the ratio calculated by CMS, $DRG_{(all\,admissions)}(j), \forall j \in J$ represents the payments for all of the admissions for each specific hospital during the period, and *NOC(i, j)* is the number of cases of each disease by hospital.

2.4 Interventions

Joynt & Jha in 2012 suggest that through holistic approaches, better financial and clinical outcomes can be achieved.[17] The literature over the last two decades shows examples of improvement in quality of care and reduction in readmissions from interventions.[18, 19] As an illustration, we screened three scientific databases for systematic literature reviews that compile clinical trials of these interventions on patients with HF. This condition was selected since it is linked with the biggest readmissions rate for Medicare patients. Table 1 shows that disease-specific interventions appear to reduce readmissions (281 randomized trials or 64%), thus our analysis builds on this assumption.

Naylor *et al.*, in 2004 concluded that interventions improving the transition of care in elderly patients would bring better clinical and financial outcomes.[20] Moreover, Hernandez *et al.*, in 2010 found that early follow-up procedures among HF patients lowered their risk of being readmitted.[21] The documented interventions focus mainly in the discharge process, follow-up process and the transition of care.[20–25] A review of the literature presenting results of interventions on HF patients is conducted (see Table 2). One of the conclusions from the review is that interventions to reduce readmissions in HF patients do not only improve the desired outcome, but also (in some cases) generate savings. Based on these results, a scenario where an intervention is applied to HF patients is simulated.

Table 1. Literature screening results supporting our assumptions

Authors	Analysis	Timeframe	Subjects	Intervention	No of studies	Conclusion
Holland *et al.*, 2005 [31]	Systematic Literature Review.	Origin to June 1, 2004	Patients with HF.	Multidisciplinary interventions.	74 RCT	Reductions in mortality and admissions.
Jovicic *et al.*, 2006 [32]	Systematic Literature Review.	Origin to Nov. 2005	Patients with HF.	Self-Management Interventions.	6 RT	Decreased overall hospital readmissions and readmissions for heart failure.
Phillips *et al.*, 2004 [33]	Meta-Analysis.	Until Oct. 2003	Patients with CHF.	Comprehensive discharge planning plus post discharge support.	18 RT	Significant reduction in readmissions.
Roccaforte *et al.*, 2005 [34]	Meta-Analysis.	Until 2004	Patients with HF.	Disease Management programs.	33 RT	Reductions in mortality and admissions.

3. Methods

In the proposed simulated scenario, an intervention is applied to all HF admissions under the IPPS of Medicare. The effects on the AF, as well as the costs, are analyzed to compare the results of implementing this disease-specific intervention with HRRP.

3.1 Simulated intervention

The intervention used in the simulated scenario consists on a single follow-up call for HF patients, made by a registered nurse. The provider checks with the patient or caregiver the adherence to the discharge plan, listens to any change in patient condition or new symptoms, adjusts the medications and suggests visit/s to the hospital as necessary. The intervention is planned to take one hour (30 min preparation, planning and recording results, and another 30 min of direct communication with the patient). The direct cost of the intervention is based on the time spent by the nurse. The mean annual and hourly wages for a registered nurse is \$67,930 and \$32.66 respectively;[26] therefore, the cost of the intervention is estimated at \$32.66. The effectiveness of the follow-up call made to HF patients is estimated using the actual reduction results published for similar interventions and included in Table 2. A triangular distribution is fitted to the data compiled from these cited interventions, resulting in a mean effectiveness, *i.e.*, reduction on 30-day preventable readmissions, of 35.8%.

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Table 2. Literature summary of interventions on HF patients

Author	Design	Setting	Participants	Intervention	Results	Conclusions
Chaudhry et al., 2010 [35]	†	33 cardiology practices around US.	1,653 patients recently hospitalized with HF.	Tele-monitoring.	Readmissions reduced by 3.85%.	Conclusions no non- statistically significant.
Cline et al., 1998 [19]	Prospective Randomized trial.	University hospital with a primary catchment area of 250,000 habitants.	190 patients (aged 65-84 years, 52.3% men), hospitalized with HF.	Education on disease, self-management and follow-up and nurse directed outpatient clinic for one year after discharge.	Longer time to readmission (141 (81) *vs.* 106 (101); $p <$ .05). Savings of $1,300 per patient annually.	Intervention decreased readmissions and costs.
Fonarow et al., 1997 [36]	†	†	214 patients with advanced HF.	Comprehensive heart failure management program.	85% reduction in readmissions. Savings of $9,800 per patient.	Intervention decreased readmissions and admissions for cardiac transplant.
Giordano et al., 2009 [37]	Randomized trial.	Cardiovascular rehabilitation departments of "Salvatore Maugeri" Foundation.	460 patients (57 +/- 10 years old) hospitalized with chronic heart failure.	Use of a portable device able to transfer a one lead trace to a cardiologists.	36% decrease in readmissions. Lower cost of readmissions (843 +/- 1,733 *vs.* 1,298 +/- 2,322).	One year HBT reduced readmissions and cost for CHF patients.
Grafft et al., 2010 [22]	Retrospective review of discharges.	Mayo Clinic hospitals in Rochester, MN.	4,989 discharges.	Hospital follow-up appointment.	†	Non appear improvement in readmissions rates.
Hansen et al., 2013 [38]	Semi controlled pre-post study.	11 hospitals varying in location, size and academic affiliation.	Target older adults.	Toolkit.	13.6% reduction in readmissions.	Intervention appeared to be associated with a decrease in readmissions rates.
Harrison et al., 2011 [23]	Retrospective cohort study.	†	30,272 patients.	Post discharge telephonic follow-up within 14 days after discharge.	23.1% less likelihood to be readmitted in the intervention group.	Intervention is effective at reducing hospital readmissions and, thus, generate potential savings.
Hernandez et al., 2010 [21]	Observational analysis.	Network of 225 hospitals.	30,136, 65 years or older patients with HF.	Physician follow-up.	Readmissions in the higher quartile of follow-up 20.9% versus 23.3% in the lower quartile.	Patients with higher physician follow up are less likely to be readmitted.
Jack et al., 2009 [39]	Randomized trial.	General medicine service at an urban, academic, safety-net hospital.	749 English speaking hospitalized adults (mean age, 49.9 years).	Nurse based follow-up, med. reconciliation, patient education. Pharmacist telephonic follow-up.	Intervention group had lower rate of hospital utilization (0.314 *vs.* 0.451)	Intervention reduced hospital utilization within 30 days of discharge.
Krumholz et al., 2002 [40]	Prospective Randomized trial.	Yale-New Haven hospital (YNHH).	88 patients (> 50 years old) with HF on admission between 10/1997 and 09/1998.	2 phases: comprehensive evaluation and education. Follow-up sessions.	39% decrease in readmissions. Saving of $7,515 per patient.	Intervention reduced readmissions and costs for patients with HF.
Naylor et al., 1999 [41]	Randomized clinical trial.	Two urban academically affiliate hospitals in Philadelphia, PA.	363 patients, hospitalized between 08/1992 and 03/1996 that had one severe medical and surgical reason for admission.	Advanced nurses deliver a comprehensive discharge planning and home follow-up protocol designed for elders at risk of poor outcomes.	Time to readmission increased in the intervention group. Fewer multiple readmissions in the intervention group (6.2% *vs.* 14.5% $p < .001$).	Intervention reduced readmissions and increase the time to be readmitted.
Naylor et al., 2004 [20]	Randomized clinical trial.	6 Philadelphia academic and community hospitals.	239 patients, 65 years old or older, with HF.	A 3 month APN-directed discharge planning and home follow-up protocol.	Time to readmissions longer in intervention group. Fewer readmissions in the intervention group (104 *vs.* 142) and lower costs ($7,636 *vs.* $12,481).	Intervention increase the time to readmission, reduce the number of hospitalizations and costs.
Rich et al., 1995 [42]	Prospective randomized trial.	Jewish hospital at Washington university medical center.	282 High risk patients, 70 years old or older, hospitalized with HF.	Comprehensive education, special diet, social service consultation, planning for an early discharge, review of medications and an intensive follow-up.	Readmissions was reduced by 56.2%.The cost of care was $460 less per patient in the intervention group.	Intervention improved quality of life and reduced hospital use and medical costs.
Riegel et al., 2002 [43]	Randomized controlled clinical trial.	†	358 patients with CHF.	Telephonic case management.	45.7% lower readmissions at 3 months, 47.8% lower at 6 months. Inpatient heart failure cost 45.5% lower at 6 months.	Intervention reduced readmissions and costs for patients. Results comparable to other pharmaceutical therapies.
Stewart, et al., 1998 [44]	Randomized trial.	Tertiary referral hospital that services a largely elderly population.	97 patients with CHF.	Single home visit (by a nurse and pharmacists) to improve medication management, identify clinical deterioration and modify follow-up and care giver vigilance.	Intervention group had lower risk of readmissions (odds ratio 0.4; 95% CI, 0.2-1.1). Intervention group had fewer days of hospitalization (261 *vs.* 452; $p = .05$).	Among a cohort of high-risk patients with CHF, intervention reduced frequency of unplanned readmissions plus out-of-hospital deaths within 6 months of discharge from the hospital.
Stewart et al., 2002 [45]	Prospective evaluation of two randomized studies.	Tertiary institution with a specialist cardiology unit.	297 patients with CHF.	First study: a structured visit by a nurse and a pharmacist. Second study: repeated visits.	Intervention had fewer readmissions (0.17 *vs.* 0.29 per month, $p < .05$). The median cost of these readmissions was A$325 versus a A$660/month.	Intervention benefits in reducing the frequency of unplanned readmissions persist in the long term and are associated with prolongation of survival.

Note. †Not explicitly mentioned in the study

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3.2 Data

The data used to study the effect of the simulated intervention comes mainly from public use files (PUF) from repositories available on the CMS website. Specifically, we used the hospital readmissions reduction programs supplemental data file and the Inpatient Medicare Provider Utilization and Payment Data for IPPS FY2013 final rule.[27] The number of hospitals considered was 3,500.

3.3 Procedure

The data contains the number of cases and excess readmissions for AMI, HF and PN, by provider and the AF for each hospital, considering the adjustment ceiling of 1% for FY2013. Then, it follows that to calculate AF we only need the base payment for each specific condition and the total payments for all admissions. However, in this study there was no access to the total payment for all admissions. Instead, we used the DRG, WIF, Labor and non-labor wages to calculate the base payment for each HRRP condition, and having the AF we use both quantities to estimate the total payments for the period. Finally, the excess of readmissions for HF after the intervention is calculated, and the AF is updated.

4. Results

4.1 Base payments

Using the described data, the base payments for the conditions considered by HRRP are calculated for each provider. The labor and non-labor wage for FY2013 were $3,679.95 and $1,668.81 respectively. The last two components are the WIF (specific for each hospital) and the DRG weights for each specific diagnosis. Table 3 shows the DRG weights considered in these calculations. The average payment, before the inclusion of the DRG weight, is $6,431.92.

Table 3. DRG codes and weight for IPPS final rule FY2013

Code	Description	Weight	Average DRG base payment
280	Acute myocardial infarction with multiple comorbidities	1.799	$ 11,576.81
281	Acute myocardial Infarction with comorbidities	1.096	$ 7,050.03
282	Acute myocardial Infarction without comorbidities or multiple comorbidities	0.773	$ 4,975.73
291	Heart failure with multiple comorbidities	1.517	$ 9,759.80
292	Heart failure with comorbidities	1.003	$ 6,453.79
293	Heart failure without comorbidities or multiple comorbidities	0.675	$ 4,342.19
193	Pneumonia with multiple comorbidities	1.489	$ 9,579.06
194	Pneumonia with comorbidities	0.999	$ 6,429.35
195	Pneumonia without comorbidities or multiple comorbidities	0.707	$ 4,552.51

Using the described data, the base payments for the conditions considered by HRRP are calculated for each provider. The labor and non-labor wage for FY2013 were $3,679.95 and $1,668.81 respectively. The last two components are the WIF (specific for each hospital) and the DRG weights for each specific diagnosis. Table 3 shows the DRG weights considered in these calculations. The average payment, before the inclusion of the DRG weight, is $6,431.92.

4.2 DRG base payment for all discharges

After the DRG base payments for each condition and for each hospital is obtained, the DRG base payment for all admissions by each hospital is computed. Results of the DRG payments for all admissions present big differences (see Table 4, showing wide variation among the hospitals serving Medicare populations).

4.3 Results from the simulated scenario

The intervention was applied to the 1,193,210 admissions for HF reported to Medicare through IPPS in FY2013. Results show that after the intervention, 710 hospitals were freed from penalization, representing a decrease of 33.43% (see Table 5). The average AF also improved from 0.0042 to 0.0039.

Table 4. Descriptive statistics for DRG all admission payments

Measurement	Value
Max	$ 711,552,145.07
Mean	$ 1,616,546.71
Min	$ 70,208,431.47
St Dev.	$ 72,055,027.96

Figure 1 shows the AF before and after the intervention for 150 providers randomly selected from the 3,500 initially considered. The behavior of the AFs was not homogeneous. Some hospitals experienced high improvement (*i.e.* provider 46), medium (*i.e.* provider 42), or no improvement (*i.e.* provider 63). Additionally, there are hospitals that after im-

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plementing the intervention were free from penalizations (*i.e.* provider 49), whereas others improved less and were unable to avoid the penalties (*i.e.* provider 72).

The intervention had a total cost of \$38.9M, while the total amount of penalties was \$253.3M. Comparing these simulated results with the actual HRRP results for the same period, a decrease of \$26.7M is observed (HRRP penalties in FY2013 were \$280M).

Table 5. Hospitals being penalized before and after the intervention

	Hospitals Penalized	% of the total	Average adjustment factor
Before Intervention	2,124	60.69	0.0042
After Intervention	1,414	40.40	0.0039

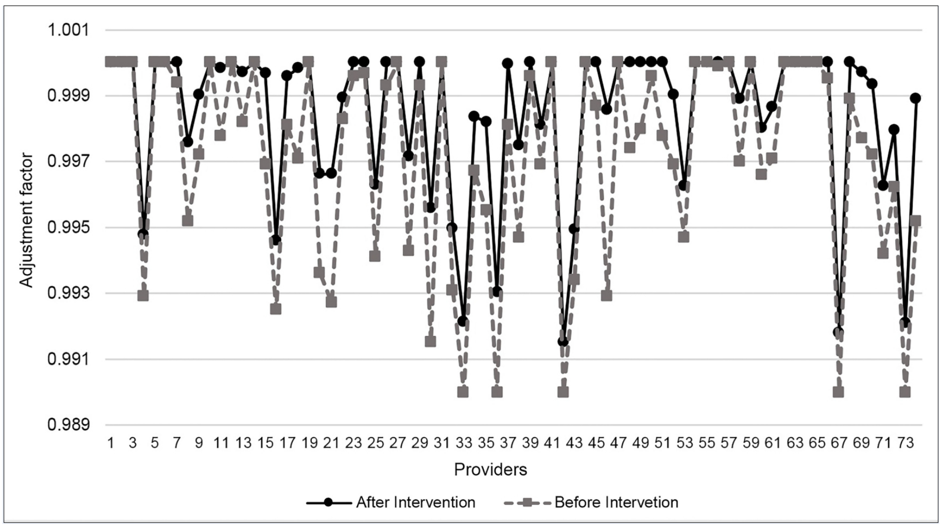

Figure 1. Adjustment ratio after and before the intervention

5. Discussion

A disease-specific intervention approach was presented as an alternative to HRRP, which is known to reduce preventable readmissions as well as to improve the quality of the delivery of care.

HRRP has been in place for three years and during that period the number of hospitals penalized has increased (see Table 6). The differences between FY2013 and FY2014 indicate that in FY2014, 11 more hospitals were penalized, while in FY2015, 413 more hospitals are penalized. These results would suggest that HRRP is not resulting in a decrease of readmission as the number of hospitals being penalized continues to increase. Conversely, a disease-specific intervention would immediately show progress by diminishing the risk of readmission for the patients, which would mean less hospitals being penalized. Results from the simulated scenario show that 710 hospitals are freed from penalties when implementing an intervention. When compared to the HRRP results for FY2013-FY2014, the simulated intervention drastically outperforms the results of HRRP.

Table 6. History of penalties through the HRRP

Title	FY2013	FY2014	FY2015
n	3,500	3,483	3,476
Cap	1%	2%	3%
Hospitals penalized	2,214	2,225	2,638
Average penalty	0.42%	0.38%	0.62%

Furthermore, a comparison of the AF between the hospitals obtaining "better results" (lower penalty) and hospitals with "worse results" (higher penalty) under HRRP, show that the number of hospitals improving decreased, while the number of hospitals that worsen increased (see Table 7). This represents a contradiction when compared with the mission of CMS which is "better healthcare, better health and lower costs through improvement".[28] A disease-specific inter-

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vention would ensure an improvement on readmission rates which would lead to, as explained by the current metrics, the number of hospitals being penalized to decrease.

Table 7. Evolution of hospitals' condition in HRRP

Title	FY2013-FY2014	FY2014-FY2015
Got Worse	1,054	2,024
%	31%	59%
Got Better	1,364	680
%	40%	20%

Meanwhile, a consistent decrease in the excess of readmissions is reported for HF throughout FY2013-FY2015. AMI also shows a decrease in the readmission rate, but just during FY2013-FY2014, while in FY2014-FY2015 there is no improvement. Reductions are found to be inconsistent for PN, as excess readmissions increased in FY2013-2014, and then decreased (see Table 8). The approach based on disease-specific interventions shows an improvement on preventable readmissions.

Considering the short timeframe that HRRP has been active, results show small and inconsistent improvements in reducing readmissions. Furthermore, it has been said that economic penalties affect more those hospitals that provide care to vulnerable patients and institutions that take the responsibility to teach and train physicians. Results from the simulation show that an approach based on disease-specific interventions would be more appropriate than HRRP because: 1) it outperforms HRRP in reducing the readmission rates; 2) by its very nature improves the quality of the delivery of care; and 3) disease-specific interventions are less costly than the penalties from HRRP.

Table 8. Evolution of hospitals' condition in HRRP

	AMI			HF			PN		
Fiscal Year rule	2013	2014	2015	2013	2014	2015	2013	2014	2015
Number of cases	500,931	492,346	505,702	1,193,210	1,161,629	1,154,060	955,611	951,383	971,906
Average (*SD*)	0.648 (.484)	0.644 (.484)	0.644 (.483)	0.890 (.324)	0.888 (.328)	0.879 (.334)	0.894 (.320)	0.897 (.315)	0.892 (.320)
Change	-	-0.62%	0%	-	-0.22%	-1.01%	-	+0.34%	-0.56%

Additionally, we presented several concerns with the methodology used by HRRP. Stone & Hoffman in 2010 point out that since hospitals bill Medicare for each discharge, there is an incentive in maximizing the discharges.[14] Moreover, reducing readmissions also reduces the hospital's revenue, which creates a conflict. A disease-specific intervention not only leads to better quality care but also translates into savings for hospitals. Increased quality of care will also lead to savings for patients as number of hospital readmissions decreases.

Joynt & Jha in 2013 found that the effects of HRRP penalties would be more severe for large hospitals, teaching hospitals and safety net hospitals.[29] Teaching hospitals represent about 25% of all participating hospitals in the IPPS. Therefore, it can be argued that the penalty approach may negatively impact the quality of medical education in the US. Instead, by applying disease-specific interventions, the quality of care for these patients improves, and avoids the negative financial impact on the hospitals. Furthermore, Berenson *et al*. in 2012 recognize that AMI, HF and PN represent about 12% of Medicare expenditures.[16] This means that in the 2013 final rule, the 12% of Medicare admissions affected the reimbursement of all the admissions billed to Medicare through the IPPS. Since disease-specific interventions focus on improvement, say by targeting excessive preventable readmissions, it could eliminate the notion of applying across the board penalties.

Finally, Burgess & Hockenberry in 2013 state that HRRP penalties will worsen the financial situation for those hospitals likely to be affected the most: large hospitals, teaching hospitals and safety net hospitals.[30] Instead, the authors advise that a policy targeting the causes of the readmissions may produce better results. The implementation of disease-specific interventions has the potential to address preventable readmissions from the mentioned perspective.

Key limitations of this study are: its short timeframe and the absence of patient-level data, which forced the use of aggregate data. Consequently, these results are not yet generalizable. However, the study does suggest (and reinforces) that an approach based on disease-specific interventions should lead to better results, better quality and less cost than HRRP. Another limitation of the this study was that the simulated scenario is applied to all hospitals, neglecting the idea that different hospitals might require different interventions.[5] However, the authors believe that these initial results encourage further work in this direction.

Future work, in addition to addressing the limitations stated

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above, could also include other disease-specific interventions, considering the unique reality, characteristics and needs of specific hospitals (or cluster of hospitals). Granted this requires access to more granular, hospital/patient specific, data. Additionally, the implementation of disease-specific interventions should ideally be as patient centered as possible. It is very likely that to properly design, model and analyze these efforts researchers will require the development and implementation of probabilistic models or decision support systems, which include patient specific data. Consequently, having access to hospital and patient-level data will enable more realistic modeling and simulation strategies that would lead to stronger and more robust implementable conclusions.

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Appendix D: Comparison of Machine Learning Algorithms for the Prediction of Preventable Hospital Readmissions (In Press, Journal for Healthcare Quality)

Comparison of machine learning algorithms for the prediction of preventable hospital readmissions

Andres Garcia-Arce[1], Florentino Rico, José L. Zayas-Castro

Abstract

A diverse universe of statistical models in the literature aim to help hospitals understand the risk factors of their preventable readmissions. However, these models are usually not necessarily applicable in other contexts, fail to achieve good discriminatory power, or cannot be compared with other models. We built and compared predictive models based on machine learning algorithms for 30-day preventable hospital readmissions of Medicare patients. This work used the same inclusion/exclusion criteria for diseases used by the Centers for Medicare & Medicaid Services. In addition, risk stratification techniques were implemented to study covariate behavior on each risk strata. The new models resulted in improved performance measured by the area under the receiver operating characteristic curve. Finally, factors such as higher length of stay (LOS), disease severity index, being discharged to a hospital, and primary language other than English were associated with increased risk to be readmitted within 30 days. In the future, better predictive models for 30-day preventable hospital readmissions can point to the development of systems that identify patients at high risk and lead to the implementation of interventions (e.g. discharge planning, follow-up) to those patients, providing consistent improvement in the quality and efficiency of the healthcare system.

Keywords

Machine learning, preventable hospital readmissions, readmission risk, predictive models, Medicare, Hospital Readmissions Reduction Program.

Conflict of interest

The Authors declare no conflict of interest or competing interest.

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[1] Corresponding author at: University of South Florida, 4202 E. Fowler Avenue, ENB 118, Tampa, FL 33620, United States. Tel.: +1 813 974 5553. E-mail address: andresg@mail.usf.edu

Author's short biosketch

Andres Garcia-Arce MIE, MSEd, is a doctoral candidate in the Department of Industrial and Management Systems Engineering at University of South Florida (USF), Tampa, FL. His primary role at USF is data scientist. Other areas of research interests include healthcare systems engineering, policy analysis and machine learning.

Jose L. Zayas-Castro, Ph.D., is Professor of Industrial and Management Systems Engineering at University of South Florida (USF), Tampa, FL. As part of his responsabilities at USF, he leads an interdisciplinary research team that conducts research, and develops curricula, in health systems engineering and improving the delivery of care to patients.

Florentino Rico Ph.D., graduate from USF currently works as Senior Specialist - Anti money laundering model risk validation at BMO Harris Bank, Chicago IL. His expertise includes data analytics, quality improvement, biostatistics and decision support systems.

Appendix D (continued)

Comparison of machine learning algorithms for the prediction of preventable hospital readmissions

Abstract

A diverse universe of statistical models in the literature aim to help hospitals understand the risk factors of their preventable readmissions. However, these models are usually not necessarily applicable in other contexts, fail to achieve good discriminatory power, or cannot be compared with other models. We built and compared predictive models based on machine learning algorithms for 30-day preventable hospital readmissions of Medicare patients. This work used the same inclusion/exclusion criteria for diseases used by the Centers for Medicare & Medicaid Services. In addition, risk stratification techniques were implemented to study covariate behavior on each risk strata. The new models resulted in improved performance measured by the area under the receiver operating characteristic curve. Finally, factors such as higher length of stay (LOS), disease severity index, being discharged to a hospital, and primary language other than English were associated with increased risk to be readmitted within 30 days. In the future, better predictive models for 30-day preventable hospital readmissions can point to the development of systems that identify patients at high risk and lead to the implementation of interventions (e.g. discharge planning, follow-up) to those patients, providing consistent improvement in the quality and efficiency of the healthcare system.

Keywords

Machine learning, preventable hospital readmissions, readmission risk, predictive models, Medicare, Hospital Readmissions Reduction Program.

Introduction

The 2010 Affordable Care Act (ACA) established the Hospital Readmissions Reduction Program (HRRP), which, since fiscal year (FY) 2013, requires the Centers for Medicare and Medicaid Services (CMS) to reduce up to 3% of reimbursements to hospitals with excessive readmissions.

More than 2,000 hospitals with high readmissions for pneumonia (PN), heart failure (HF), and acute myocardial infarction (AMI) have been penalized with payment adjustments [1]. Under the HRRP, the maximum penalty was increased to 3% in 2015 and new conditions were added [2]. These include chronic obstructive pulmonary disease (COPD), total hip arthroplasty (THA), and total knee arthroplasty (TKA). Starting in FY2017, coronary artery bypass graft (CABG) will be added to the list of targeted conditions for the reduction of readmissions.

The preliminary results from some states suggest a decrease in readmissions [3], whereas aggregated data does not show a decreasing pattern over the first three years of HRRP [4]. Furthermore, the implementation of the HRRP leveraged certain criticisms—for example, that safety-net hospitals were disproportionally impacted by penalties [5], endangering the quality of care for those in need. The reduction of preventable readmissions has become a priority for hospitals seeking to avoid CMS penalties. It is thus a necessity to invest in research and development of systems capable of 1) identifying patients at high risk of readmission and 2) targeting interventions to reduce readmissions by improving patient discharge, care coordination and ultimately quality of care.

Review of Literature

Most research studies have concentrated on identifying patients at risk of readmission using predictive models. Kansagara et al. [6] conducted a systematic review of risk prediction models for hospital readmission. The studies vary by readmission timeframe (i.e., 15 days to 12 months after index discharge), population setting (i.e., age range, Medicare, Medicaid), geographical reach (i.e., nationwide, statewide, hospital specific), and source of data (i.e., administrative claims data, real time data and clinical data). However, only one study attempted to identify potentially preventable readmissions. Furthermore, the majority of the readmission predictive models perform poorly, measured by the area under the curve (AUC) of the receiver operating characteristic (ROC) reported values, between 0.5 and 0.7. But, to make inferences an AUC equal to, or greater than 0.8 is preferred.

The three predictive models created for the CMS showed relatively low discriminatory capacity, with an AUC equal to 0.61, 0.63, and 0.63 for HF, AMI, and PN, respectively [7–9]. Shulan, Gao and Moore [10] obtained the highest AUC (0.8) among published studies in prediction of all-cause readmissions using administrative claims data. This study applied a logistic regression (LR) model using inpatient data from Veterans Healthcare Network in New York and was validated by a 2 cross-fold method, obtaining an AUC of 0.79.

Fernandez-Delgado et al.[11] studied a wide range of classifiers and predictive algorithms, including LR and machine learning algorithms, reporting that random forest shows the best results. Kulkarni, Smith and Woeltje [12] compared decision trees, neural networks, and LR models to predict risk of readmission using patient administrative data. Their results suggest that machine learning algorithms can improve the AUC of LR. In addition, Au et al.[13] reported that even simpler models, like LACE (a scoring model using the length of stay, acuity of admission, comorbidities, and previous emergency department visits), outperform the CMS models.

More recent studies dig into the application of machine learning algorithms in predicting readmissions. For instance, Yu et al.[14] compare time to event modeling (Cox model) with support vector machine (SVM) and LACE model (business standard model) to predict AMI, PN, HF, and all-cause readmissions, reporting that SVM outperforms the other models. Also, Vedomske, Brown and Harrison [15] developed a predictive model for HF readmissions based on random forest, reporting better performance (AUC = 0.84) using diagnosis and procedures as input variables.

In summary, abundant research explores the use of different predictive models to improve the predictive performance of readmissions. However, these models use different disease “inclusion/exclusion criteria” than the one specified by CMS. Furthermore, the use of machine learning models to predict readmission has still not been sufficiently explored.

This research builds and compares different predictive models based on machine learning algorithms for preventable hospital readmissions, which represents an important milestone in the pursuit of better tools to provide hospitals the necessary means to advance their understanding and reduction of preventable readmissions.

Appendix D (continued)

Purpose

This study explored the potential of machine learning algorithms to assist in the prediction of 30-day preventable readmissions. Different predictive models were built based on support vector machine, random forest, gradient-boosted trees, and neural network. These four techniques/algorithms were chosen based on previous research and are compared with LR in terms of their predictive power. Additionally, risk stratification techniques were used to identify groups of patients at a high or low risk of readmission. Finally, patient differences within those groups will be discussed.

Study design and methods

<u>*Data source and variables*</u>

We used the administrative claims dataset of a network of 11 hospitals from January 2005 to July 2012. The network of hospitals includes general, teaching, and specialty hospitals located in three adjacent counties in Florida. The initial dataset had 1,093,177 records for hospital admissions from 594,751 patients. Figure 1 shows the steps used to select the cohorts of patients and eliminate records related to planned and/or unpreventable readmissions. The inclusion/exclusion criteria for ICD-9 codes and diseases mimics the CMS criteria and also the work done by Rico et al.[16] , which we will compare with models built in this work. The diseases included in the study are AMI, PN, congestive heart failure (CHF), chronic obstructive pulmonary disease (COPD), and type 2 diabetes (DIA). The disease cohorts were extracted from the raw dataset by using ICD-9 codes. For AMI, the codes used were those beginning in 410; for CHF, 428.*, 402.01, 404.01, 404.03, 404.11, 404.13, 404.91, and 404.93; for COPD, 491.0, 491.1, 491.2, 491.20, 491.21, 490, 496, and 492; for DIA, 410.*; and for PN, 480–483, 485–486, 510, 511.0, 511.1, 511.9, a primary diagnosis of PN-related symptoms (780.6, 786.00, 786.05, 786.06, 786.07, 786.2, 786.3, 786.4, 786.5, 786.51, 786.52, and 786.7), and a secondary diagnosis of pneumonia, emphysema, or pleurisy.

[**Figure 1** Procedure to exclude unavoidable and planned admission records]

The dataset originally had 119 fields, but after review of the literature and discussion with hospital experts, 17 independent variables were selected as predictors in the model. The descriptive statistics of the independent variable candidates are reported in Table 1. During the data processing, a variable coded as “behavioral health” was included to account for behavioral comorbidities.

[Table 1. Descriptive statistics for independent candidate variables]

<u>*Modeling and analysis*</u>

Using the software R and the functions available in the R Package caret [17], we separated each disease cohort dataset into training and testing sets. We then trained a LR with stepwise variable selection using the training sets. The resultant models were used to predict in the testing set, and AUC from ROC values were used as baselines for the performance of the machine learning.

Next, using the same training sets, a random forest (RF) model, a stochastic gradient-boosted model (GBM), a support vector machine (SVM) model, and a neural network (NN) model were trained. To further inspect the performance of each model, tuning was conducted to seek the best model parameters. To obtain the performance of each of candidate model, we used repeated 10-fold cross validation on the training set.

While training these models, two issues were also explored: the imbalanced nature of the response variable in the cohort datasets and the harm that "unimportant" variables could produce to models such as SVM and NN. To explore the first concern, the synthetic minority oversampling technique (SMOTE), introduced by Chawla and Bowyer [18] was used to create new balanced training sets that were used to train models. A feature selection tool called BORUTA [19] was utilized to assess variable importance, which led to the use of fewer variables in order to improve the results of the predictive models.

After training all models, a single model was selected for each cohort based on their AUC. The model was used to predict in the testing set and then compared to the LR models. Figure 2 depicts the process of analysis we followed, and the results are presented in the next section.

[Figure 2. Predictive model building and selection procedure]

Finally, using the predicted risk of readmission, patients were classified into three clusters of equal size: high risk, moderate risk, and low risk. The differences in patients belonging to each stratum were determined.

Institutional Review Board Approval

This project was exempted by the Institutional Review Board because it does not meet the definition of research involving human subjects (IRB# Pro00027173).

Results

Appendix D (continued)

<u>*Assessment of the predictive models*</u>

First, we fitted the LR model to the different cohorts of diseases. This was performed as a way to replicate the methodology presented by Rico et al.[16], who used LR models to identify risk factors for the same diseases. The performances from the replicated LR models were used as baseline in our comparison.

[Table 2. Comparison of models by disease]

Table 2 summarizes the performance (as measured by AUC) of the best models for each family of models by disease. As shown, SVM models did not outperform any other method in any disease. Furthermore, NN models always outperformed LR in all diseases, while for PN, the NN model was the only one that outperformed LR. In no case did use of the SMOTE technique lead to better AUC, whereas in the case of COPD and DIA, the use of BORUTA yielded better results in the prediction. The highest improvement in terms of AUC was in DIA, while the lowest was for CHF.

[Table 3. Performance of selected models]

Table 3 shows the AUC obtained for each “best” machine learning model and LR model in the testing set. The confidence intervals obtained through bootstrapping are also provided. For the considered diseases, machine learning models present a small improvement in the predictive performance measured by the AUC. In general, NN-based models show better performance when predicting readmission, except for CHF (where GBM outperforms NN).

<u>*Risk stratification analysis*</u>

Table 4 presents the results for the descriptive and test statistics results for the variables in each risk strata for AMI patients. The first impression is that the risk of readmission increases by strata, as does the number of admissions, the LOS, and the Charlson score. In addition, a greater variance can be seen in higher risk groups.

[Table 4. Description of risk strata for AMI]

In terms of the statistical significance of the variables, some lost significance as the risk strata went from low to high. As an example, in AMI, increased age is found to be significant in the low risk strata, whereas it is not significant in the higher risk strata. Another example is spoken language; although we know it is considered important, it is not significant in the high risk strata.

AMI patients at higher risk of readmission present certain characteristics, such as Medicare insured, discharged to the hospital or non-acute facilities, divorced or widowed, having an increased number of previous admissions, and experiencing longer LOS.

Table 5 in the Appendix contains the risk stratification analysis for the rest of the conditions considered in this article. Generally speaking, the risk of readmission increases following the same pattern found for AMI. Specifically, in COPD patients, the number of previous admissions is statistically significant, and the variance is less than that reported for the rest of the conditions. The Charlson score matches the previous behavior for PN, DIA, COPD, and CHF.

Being discharged to a non-acute facility was associated with higher readmission risk for COPD, PN, and COPD. Patients with DIA and PN presenting as non-commercial payers were also found to be at high risk. PHLOTE was associated with increased risk of readmission for COPD, CHF, PN, and DIA. Finally, a higher disease severity index was associated with readmission.

Discussion

To summarize, we developed and compared predictive models using machine learning algorithms that can improve the prediction of readmission for specific diseases. Depending on the disease, various factors increasing the risk of readmission were determined from the proposed models. Such factors were LOS, Charlson score, PHLOTE, type of insurance, and disease severity index.

Some of the risk factors found in this work could be used as targets for disease-specific interventions. For example, improved care coordination for patients with multiple conditions, specific follow-up for the most severe patients, and improved discharge instructions for non-native English speaker patients could reduce the risk of readmission. Additionally, although there may be some debate about this, the significance of type of insurance could be interpreted as a socioeconomic factor influencing the risk of readmission [10,20]. This insight can provide support to the claim that HRRP should consider a specific adjustment that accounts for the various socioeconomic factors influencing readmission risk [21,22].

In terms of predictive power, our work can be compared with other published models reporting better results [10,12,23]. However, these models consider either fewer admissions, fewer years of data and/or less recent data, or fewer collection sites; these factors make these models less generalizable than those proposed in this article. Even in the case of Vedomske el at. [15], who achieved an AUC of 0.84, only used one ICD-9 code (428.0) for inclusion in the study cohort , whereas our model considers the inclusion/exclusion criteria released by CMS to include patients in the cohort of heart failure (eight different ICD-9 codes).[8] Furthermore, our model uses 2.5 years more of data, which also is two years more recent.

In conclusion, this work built and compared prediction models based on four heavily used machine learning algorithms, ranking them by performance (AUC) and significantly improving upon the CMS models. We found NN models to perform better when predicting readmissions. Additionally, the risk stratification analysis yielded the finding that, in general, disease severity, higher number of previous admissions, having PHLOTE, being insured by a non-commercial agency, and being discharged to a non-acute facility were factors that increased the risk of readmission. These insights can be used to design disease-specific interventions to decrease the readmission of high-risk patients.

Limitations

Some limitations of this work are acknowledged. For the predictive model training, we used data collected for seven years (until 2012) from 11 institutions in Florida, while current CMS models consider more years of nationwide data. Also, because of the nature of readmissions, the occurrence of this event in the dataset has a low frequency compared to the other class (non-readmitted). Therefore, prediction of readmission becomes a difficult problem and requires further exploration. Finally, although the healthcare community is slowly moving into the data science world, machine learning algorithms are still out of reach for most practitioners, which could present a challenge when implementing these models.

Directions for Future Research

Further research will include the validation of the models in a cross-sectional setting. Additionally, we recommend to use more heterogeneous and high dimensional data, seeking for the inclusion of more variables in the model that could yield better results. Finally, in this work we addressed the issue of unbalanced data by applying the SMOTE algorithm, although without improving the prediction. In future research, the readmission prediction could be considered as an anomaly detection problem, which lends itself to exploration by other statistical methods that could yield even better results.

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Appendix

[Table 5: Results by risk strata for COPD, CHF, PN, and DIA]

Appendix D (continued)

[Table 1 - Descriptive statistics for independent candidate variables]

Variable	Levels	AMI (11,205)	CHF (9,586)	COPD (7,911)	DIA (6,145)	PN (12,123)
Readmitted	Yes	2,003 (18%)	1,532 (16%)	1,155 (15%)	751 (12%)	1,361 (11%)
	No	9,202 (82%)	8,054 (84%)	6,756 (85%)	5,394 (88%)	10,762 (89%)
Admission Number: mean (sd)		1.87 (1.85)	2.79 (2.69)	3.31 (3.61)	3.10 (4.50)	2.4 (3.00)
Year	H	1,669 (15%)	1,847 (19%)	1,050 (13%)	881 (14%)	1,949 (16%)
	I	1,492 (13%)	1,537 (16%)	959 (12%)	826 (13%)	1,765 (15%)
	J	1,745 (16%)	1,269 (13%)	952 (12%)	819 (13%)	1,664 (14%)
	K	1,830 (16%)	1,313 (14%)	1,169 (15%)	905 (15%)	1,706 (14%)
	L	1,680 (15%)	1,189 (12%)	1,350 (17%)	957 (16%)	1,819 (15%)
	M	1,634 (15%)	1,398 (15%)	1,369 (17%)	976 (16%)	1,870 (15%)
	N&O	1,155 (10%)	1,033 (11%)	1,062 (13%)	781 (13%)	1,350 (11%)
Length of Stay: mean(sd)		4.09 (4.05)	4.57 (4.61)	3.81 (3.48)	3.85 (4.89)	5.16 (4.73)
Admission Type	Emergency	8,659 (77%)	8,024 (84%)	6,501 (82%)	4,267 (69%)	10,597 (87%)
	Other	233 (2%)	430 (4%)	720 (9%)	1,115 (18%)	369 (3%)
	Routine	1,034 (9%)	634 (7%)	288 (4%)	327 (5%)	513 (4%)
	Urgent	1,279 (11%)	498 (5%)	402 (5%)	436 (7%)	644 (5%)
Behavioral Health Comorbidity index	Yes	2,232 (20%)	2,250 (23%)	2,749 (35%)	1,550 (25%)	3,606 (30%)
	No	8,973 (80%)	7,336 (77%)	5,162 (65%)	4,595 (75%)	8,517 (70%)
Marital Status	Divorced or Separated	1,173 (10%)	1,019 (11%)	1,565 (20%)	960 (16%)	1,440 (12%)
	Legally Married	5,739 (51%)	3,851 (40%)	2,800 (35%)	2,185 (36%)	5,043 (42%)
	Single	2,547 (23%)	2,071 (22%)	1,857 (23%)	2,230 (36%)	3,279 (27%)
	Widowed	1,746 (16%)	2,645 (28%)	1,689 (21%)	770 (13%)	2,361 (19%)
Discharge Disposition	Non Acute Facility	2,959 (26%)	4,126 (43%)	2,341 (30%)	2,001 (33%)	4,099 (34%)
	Routine	6,413 (57%)	5,054 (53%)	5,306 (67%)	3,933 (64%)	7,689 (63%)
	Hospital or Specialist	1,680 (15%)	277 (3%)	79 (1%)	61 (1%)	107 (1%)
	No Treatment or other	153 (1%)	129 (1%)	185 (2%)	150 (2%)	228 (2%)
Age	[18,45)	853 (8%)	480 (5%)	364 (5%)	1,472 (24%)	2,018 (17%)
	[45,55)	1,988 (18%)	920 (10%)	1,163 (15%)	1,407 (23%)	1,785 (15%)
	[55,65)	2,573 (23%)	1,267 (13%)	1,880 (24%)	1,166 (19%)	1,813 (15%)
	[65,75)	2,262 (20%)	1,659 (17%)	1,993 (25%)	915 (15%)	1,861 (15%)
	[75,85)	2,289 (20%)	2,744 (29%)	1,773 (22%)	763 (12%)	2,639 (22%)

Appendix D (continued)

Variable	Levels	AMI (11,205)	CHF (9,586)	COPD (7,911)	DIA (6,145)	PN (12,123)
	[85,)	655 (6%)	1,417 (15%)	479 (6%)	245 (4%)	1,118 (9%)
	Null	585 (5%)	1,099 (11%)	259 (3%)	177 (3%)	889 (7%)
Payer Class	Commercial	2,972 (27%)	910 (9%)	868 (11%)	1,228 (20%)	2,229 (18%)
	Medicaid	923 (8%)	988 (10%)	1,143 (14%)	1,301 (21%)	1,522 (13%)
	Medicare	6,274 (56%)	7,277 (76%)	5,337 (67%)	2,747 (45%)	7,275 (60%)
	Self-Payment or other	1,036 (9%)	411 (4%)	563 (7%)	869 (14%)	1,097 (9%)
Race	Black	699 (6%)	1,467 (15%)	696 (9%)	1,714 (28%)	1,403 (12%)
	White	9,211 (82%)	7,198 (75%)	6,734 (85%)	3,497 (57%)	9,444 (78%)
	Hispanic	924 (8%)	781 (8%)	380 (5%)	809 (13%)	1,055 (9%)
	Other or Null	371 (3%)	140 (1%)	101 (1%)	125 (2%)	221 (2%)
Language	English	8,814 (79%)	6,729 (70%)	6,295 (80%)	4,814 (78%)	9,112 (75%)
	Other or Null	2,391 (21%)	2,857 (30%)	1,616 (20%)	1,331 (22%)	3,011 (25%)
Sex	Female	4,635 (41%)	4,953 (52%)	4,566 (58%)	3,039 (49%)	6,753 (56%)
	Male	6,570 (59%)	4,633 (48%)	3,345 (42%)	3,106 (51%)	5,370 (44%)
Disease Severity Index	Minor	2,826 (25%)	897 (9%)	1,605 (20%)	1,330 (22%)	1,315 (11%)
	Moderate	4,589 (41%)	4,343 (45%)	3,424 (43%)	2,086 (34%)	5,872 (48%)
	Severe	2,548 (23%)	3,388 (35%)	1,921 (24%)	1,430 (23%)	3,827 (32%)
	Extreme	1,014 (9%)	529 (6%)	241 (3%)	185 (3%)	740 (6%)
	Null	228 (2%)	429 (4%)	720 (9%)	1,114 (18%)	369 (3%) [1]

[1] Because of rounding, some percentages might not add to 100%.

Appendix D (continued)

[Table 2 - Comparison of predictive models]

	AMI	PN	COPD	CHF	DIA
LR	0.7328	0.6461**	0.684	0.6237***	0.6702***
NN	0.7518*	0.6546*	0.6988*	0.6248**	0.6957*
SVM	0.7074	0.5598	0.611	0.5728	0.6123
GBM	0.7510**	0.6442***	0.6850**	0.6314*	0.6829**
RF	0.747***	0.6325	0.6686***	0.6	0.6699

(* Best model, ** Second Best model, *** Third best model).

Appendix D (continued)

[Table 3 – Performance of selected models]

Disease cohort	LR replication AUC (CI)	Model Chosen	Characteristics	Proposed model AUC (CI)
AMI	0.7328 (0.7044-0.7604)	NN (size=5, decay=0.1)	Raw (no SMOTE), no BORUTA	0.7518 (0.7247-0.7782)
COPD	0.6840 (0.6494-0.7173)	NN (size=10, decay=2)	Raw, BORUTA	0.6988 (0.6669-0.7291)
CHF	0.6237 (0.5944-0.6537)	GBM (n.trees=100, interaction.depth=1, shrinkage=0.1, n.minobsinnode=10)	Raw, no BORUTA	0.6314 (0.6001-0.6622)
PN	0.6461 (0.6149-0.6758)	NN (size=1, decay=0.1)	Raw, no BORUTA	0.6546 (0.6246-0.6859)
DIA	0.6702 (0.6285-0.7131)	NN (size=2, decay=2)	Raw, BORUTA	0.6957 (0.6569-0.7359)

Appendix D (continued)

[Table 4 - Description of risk strata for AMI]

	Low (N=881)	p value	Moderate (N=881)	p value	High (N=881)	p value
Admission number: Mean(Sd)	1.304 (0.689)	1.09E-6	1.736(1.047)	7.27E-15	2.763 (3.567)	2E-16
Charlson score	0.79 (1.021)	1.10E-10	1.347 (1.419)	0.000816	1.911 (1.830)	0.819249
Length of Stay	2.914 (2.201)	0.92254	4.118 (2.992)	2E-16	5.006 (5.039)	2E-16
Marital Status: n (%)		2.41E-7		0.000119		2.75E-9
Divorced or separated	70 (8%)		104 (12%)		125 (14%)	
Married	466 (53%)		481 (55%)		426 (48%)	
Single	279 (32%)		184 (21%)		166 (19%)	
Widowed	66 (7%)		112 (13%)		164 (19%)	
Admission type		2.60E-9		8.12E-7		3.91E-3
Emergency	613 (70%)		668 (76%)		747 (85%)	
Other	16 (2%)		9 (1%)		25 (3%)	
Routine	102 (12%)		98 (11%)		35 (4%)	
Urgent	150 (17%)		106 (12%)		74 (8%)	
Discharge disposition		2E-16		2E-16		2E-16
Hospital	0 (0%)		37 (4%)		384 (44%)	
Non Acute Facility	54 (6%)		242 (27%)		324 (37%)	
Null	0 (0%)		0 (0%)		1 (0%)	
Routine	827 (94%)		591 (67%)		143 (16%)	
Specialized Facility	0 (0%)		2 (0%)		1 (0%)	
Without Treatment	0 (0%)		9 (1%)		28 (3%)	
Age		3.27E-7		0.053324		0.014162
[18,45)	67 (8%)		62 (8%)		46 (5%)	
[45,55)	194 (22%)		134 (15%)		131 (15%)	
[55,65)	277 (31%)		195 (22%)		170 (19%)	
[65,75)	179 (20%)		208 (24%)		227 (26%)	
[75,85)	127 (14%)		201 (23%)		228 (26%)	
[85,)	37 (4%)		81 (9%)		79 (9%)	
NULL	0 (0%)		0 (0%)		0 (0%)	
Payer class		5.18E-12		0.1905		1.65E-7
Commercial	320 (36%)		209 (23%)		170 (19%)	
Medicaid	79 (8%)		71 (8%)		72 (8%)	
Medicare	346 (39%)		511 (58%)		585 (66%)	
Null Payer	12 (1%)		4 (0%)		7 (0%)	
Pending	98 (11%)		78 (8%)		38 (4%)	
Self pay	26 (2%)		8 (0%)		9 (1%)	
Race		1.65E-11		9.61E-10		5.99E-1
Black	48 (5%)		68 (7%)		67 (7%)	
White	735 (83%)		693 (78%)		697 (79%)	
Hispanic	59 (6%)		88 (9%)		92 (10%)	
Other or Null	39 (4%)		32 (3%)		25 (2%)	
Primary Language		2.74E-15		2E-16		0.213687
English	801 (90%)		671 (76%)		627 (71%)	
Other or Null	80 (9%)		210 (23%)		254 (28%)	
Gender		4.20E-16		2E-16		0.060555

Appendix D (continued)

	Low (N=881)	p value	Moderate (N=881)	p value	High (N=881)	p value
Male	208 (23%)		389 (44%)		467 (53%)	
Female	673 (76%)		492 (55%)		414 (46%)	
Disease severity index		7.36E-16		2E-16		3.34E-6
Minor	350 (39%)		192 (21%)		161 (18%)	
Moderate	358 (40%)		407 (46%)		337 (38%)	
Major	138 (15%)		223 (25%)		204 (23%)	
Extreme	19 (2%)		51 (5%)		154 (17%)	
Null	16 (1%)		8 (0%)		25 (2%)	

Appendix D (continued)

[Table 5 - Results by risk strata for COPD, HF, PN and DIA]

	COPD						CHF					
	Low (N=659)	p value	Moderate (N=659)	p value	High (N=659)	p value	Low (N=798)	p value	Moderate (N=798)	p value	High (N=798)	p value
Admission number: Mean(Sd)	1.31(0.57)	2E-16	2.23(1.34)	2E-16	6.24(4.79)	2E-16	1.37(0.63)	2E-16	2.05(1.16)	2E-16	4.73(3.58)	2E-16
Charlson score	1.41(0.7)	2E-16	1.84(1.06)	0.1172	2.62(1.39)	2.20E-16	1.39(1.29)	2E-16	1.94(1.42)	2.08E-9	2.95(1.54)	0.01197
Length of Stay	2.46(1.81)	2E-16	3.68(2.47)	2E-16	5.59(5.02)	2E-16	3.11(2.25)	2E-16	4.4(3.19)	2E-16	6.38(8.40)	9.53E-13
Marital Status: n (%)		2E-16		2E-16				2E-16		0.00037		0.05801
Divorced or separated	89(13)		142(21)		164(24)		83(10)		74(9)		87(10)	
Married	318(48)		215(32)		166(25)		346(43)		315(39)		301(37)	
Single	140(21)		160(24)		168(25)		209(26)		162(20)		146(18)	
Widowed	112(16)		142(21)		161(24)		160(20)		247(30)		264(33)	
Admission Type		2E-16		4.54E-5		3.15E-5		2E-16		0.161064		2.15E-5
Emergency	495(75)		555(84)		588(89)		649(81)		657(82)		700(87)	
Other	103(15)		46(6)		23(3)		64(8)		20(2)		19(2)	
Routine	19(2)		32(4)		19(2)		42(5)		74(9)		43(5)	
Urgent	42(6)		26(3)		29(4)		43(5)		47(5)		36(4)	
Discharge disposition		2E-16		2E-16		2E-16		2E-16		2E-16		2E-16
Non Acute Facility	72(10)		216(32)		323(49)		171(21)		372(46)		482(60)	
Null or Non treatment	583(88)		420(63)		294(44)		624(78)		417(52)		235(29)	
Routine	1(0)		6(0)		9(1)		0(0)		0(0)		69(8)	
Specialized Facility or Hospital	3(0)		17(2)		33(5)		3(0)		9(1)		12(1)	
Age		2E-16		2E-16		2E-16		2E-16		2E-16		0.01806
[18,45)	40(6)		29(4)		17(2)		55(6)		29(3)		47(5)	
[45,55)	94(14)		103(15)		108(16)		108(13)		49(6)		63(7)	
[55,65)	202(30)		149(22)		131(19)		163(20)		84(10)		92(11)	
[65,75)	166(25)		174(26)		161(24)		134(16)		150(18)		115(14)	
[75,85)	135(20)		158(23)		129(19)		205(25)		260(32)		224(28)	

Appendix D (continued)

	COPD						CHF					
	Low (N=659)	p value	Moderate (N=659)	p value	High (N=659)	p value	Low (N=798)	p value	Moderate (N=798)	p value	High (N=798)	p value
[85,)	10(1)		27(4)		88(13)		67(8)		128(16)		148(18)	
NULL	12(1)		19(2)		25(3)		66(8)		98(12)		109(13)	
Payer class		2E-16		2E-16		1.21E-12		2E-16		6.53E-6		0.70357
Commercial	142(21)		45(6)		30(4)		138(17)		55(6)		46(5)	
Medicaid	37(5)		112(16)		131(19)		81(10)		70(8)		93(11)	
Medicare	406(61)		466(70)		469(71)		502(62)		655(82)		646(80)	
Null, Pending or Self Payer	74(11)		36(5)		29(4)		77(9)		18(2)		13(1)	
Race		3.15E-5		8.28E-4		0.0676		0.0007		0.014731		0.00126
Black	62(9)		64(9)		61(9)		133(16)		104(13)		133(16)	
White	558(84)		544(82)		554(84)		591(74)		613(76)		590(73)	
Hispanic	25(3)		40(6)		35(5)		47(5)		68(8)		69(8)	
Other or Null	14(2)		11(1)		9(1)		27(3)		13(1)		6(0)	
Language		2E-16		2E-16		5.76E-15		2E-16		2E-16		2E-16
English	601(91)		490(74)		496(75)		721(90)		451(56)		494(61)	
Other or Null	58(8)		169(25)		163(24)		77(9)		347(43)		304(38)	
Gender		0.704		0.20729		0.991		0.2873		0.444442		0.28694
Male	373(56)		391(59)		374(56)		415(52)		377(47)		364(45)	
Female	286(43)		268(40)		285(43)		383(47)		421(52)		434(54)	
Disease severity index		2E-16		2E-16		2E-16		3.03E-9		9.43E-7		1.19E-10
Minor	209(31)		137(20)		81(12)		103(12)		75(9)		45(5)	
Moderate	289(43)		306(46)		267(40)		360(45)		391(48)		337(42)	
Major	53(8)		153(23)		239(36)		244(30)		279(34)		329(41)	
Extreme	5(0)		17(2)		49(7)		27(3)		33(4)		68(8)	
Null	103(15)		46(6)		23(3)		64(8)		20(2)		19(2)	

Appendix D (continued)

	PN						DIA					
	Low (N=1,010)	p value	Moderate (N=1,010)	p value	High (N=1,010)	p value	Low (N=511)	p value	Moderate (N=511)	p value	High (N=511)	p value
Admission number: Mean(Sd)	1.292(0.607)	2E-16	1.798(1.177)	2E-16	4.164(4.709)	2E-16	1.192(0.475)	2E-16	1.912(1.073)	2E-16	5.996(6.255)	2E-16
Charlson score	0.671(0.778)	2E-16	1.213(1.039)	2E-16	2.188(1.513)	2E-16	1.061(0.766)	2E-16	2.229(1.459)	2E-16	3.352(1.387)	0.008429
Length of Stay	3.182(2.071)	2E-16	4.727(2.885)	2E-16	7.459(7.525)	2E-16	1.795(1.743)	2E-16	3.703(3.432)	2E-16	6.456(7.794)	2E-16
Marital Status: n (%)		2E-16		2E-16		2E-16		2E-16		0.1021		2E-16
Divorced or eparated	69(6)		107(10)		173(17)		44(8)		68(13)		123(24)	
Married	517(51)		423(41)		338(33)		203(39)		195(38)		146(28)	
Single	320(31)		244(24)		258(25)		222(43)		142(27)		184(36)	
Widowed	104(10)		236(23)		241(23)		42(8)		106(20)		58(11)	
Admission type		2E-16		2E-16		1.38E-14		2E-16		6.29E-11		0.003284
Emergency	837(82)		891(88)		916(90)		302(59)		369(72)		415(81)	
Other	68(6)		12(1)		6(0)		149(29)		65(12)		43(8)	
Routine	44(4)		46(4)		35(3)		12(2)		37(7)		35(6)	
Urgent	61(6)		61(6)		53(5)		48(9)		40(7)		18(3)	
Discharge disposition		2E-16		2E-16		2E-16		2E-16		8.57E-16		1.09E-10
Non Acute Facility	76(7)		343(33)		637(63)		50(9)		212(41)		244(47)	
Null or Non Treatment	934(92)		661(65)		297(29)		454(88)		287(56)		242(47)	
Routine	0(0)		0(0)		29(2)		1(0)		0(0)		4(0)	
Specialized facility or Hospital	0(0)		6(0)		47(4)		6(1)		12(2)		21(4)	
Age		2E-16		2E-16		7.91E-14		2E-16		2E-16		2E-16
[18,45)	282(27)		111(10)		111(10)		157(30)		94(18)		120(23)	
[45,55)	165(16)		128(12)		164(16)		109(21)		75(14)		155(30)	
[55,65)	209(20)		140(13)		111(10)		122(23)		101(19)		61(11)	
[65,75)	128(12)		180(17)		133(13)		57(11)		114(22)		61(11)	
[75,85)	144(14)		251(24)		267(26)		31(6)		87(17)		76(14)	
[85,)	46(4)		110(10)		128(12)		18(3)		30(5)		32(6)	

Appendix D (continued)

	PN						DIA					
	Low (N=1,010)	p value	Moderate (N=1,010)	p value	High (N=1,010)	p value	Low (N=511)	p value	Moderate (N=511)	p value	High (N=511)	p value
NULL	36(3)		90(8)		96(9)		17(3)		10(1)		6(1)	
Payer class		2E-16		2E-16		2E-16		2E-16		6.65E-15		0.000125
Commercial	396(39)		99(9)		55(5)		163(31)		73(14)		71(13)	
Medicaid	68(6)		145(14)		174(17)		82(16)		89(17)		139(27)	
Medicare	348(34)		718(71)		745(73)		132(25)		294(57)		267(52)	
Null, Pending or Self Payer	198(19)		48(4)		36(3)		134(26)		55(10)		34(6)	
Race		2E-16		2E-16		4.44E-5		0.431		0.5005		0.037051
Black	132(13)		119(11)		124(12)		169(33)		117(22)		129(25)	
White	722(71)		807(79)		811(80)		258(50)		308(60)		332(64)	
Hispanic	116(11)		75(7)		68(6)		68(13)		73(14)		48(9)	
Other or Null	40(3)		9(0)		7(0)		16(3)		13(2)		2(0)	
Language		1.75E-7		6.85E-8		0.4956		2E-16		4.60E-5		4.10E-6
English	825(81)		722(71)		731(72)		440(86)		386(75)		388(75)	
Other or Null	185(18)		288(28)		279(27)		71(13)		125(24)		123(24)	
Gender		2E-16		2E-16		2E-16		0.771		0.5612		0.939978
Male	392(38)		412(40)		525(51)		268(52)		255(49)		240(46)	
Female	618(61)		598(59)		485(48)		243(47)		256(50)		271(53)	
Disease severity index		2E-16		2E-16		2E-16		2E-16		1.09E-8		0.075632
Minor	190(18)		90(8)		43(4)		168(32)		91(17)		78(15)	
Moderate	628(62)		549(54)		323(31)		120(23)		208(40)		190(37)	
Major	121(11)		338(33)		493(48)		72(14)		133(26)		161(31)	
Extreme	3(0)		21(2)		145(14)		2(0)		14(2)		39(7)	
Null	68(6)		12(1)		6(0)		149(29)		65(12)		43(8)	