PREFERRED POST-ACUTE PROVIDER NETWORK: AN APPROACH TO BUILD CARE COORDINATION BETWEEN ACUTE CARE AND POST-ACUTE CARE FACILITIES

A Dissertation

by

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ABSTRACT

The rate of patient discharge to post-acute care (PAC) facilities has grown abruptly in the last few years, contributing to increased healthcare costs. Although PAC benefits include better clinical outcomes and lower readmission and mortality, the variation in referral patterns raises concerns about substandard care and inflated costs. To mitigate these issues, building a preferred PAC provider network (PPN) as a partnership between acute care hospitals (ACH) and PAC providers is a long due necessity. However, the formation of this integrated network is complex involving uncertainty from various aspects. It requires a clear understanding of referral patterns to PAC providers, PAC quality performance, and PAC providers capacity and ability to serve patients from specific geographies and varying acuity levels. To carry out an investigative effort to address these complexities is the overarching theme of this research.

This research develops a data-driven standardized predictive model to help providers predict the PAC destination and quantify the risk factors influencing PAC referral. The study applies multinomial logistic regression to develop the predictive model. This study further investigates the common and interrelated risk factors for readmission and length of stay of the patients in acute hospitals with an association of PAC destinations. The last part of this research formulates an operational planning and resource adjustment model to build a PAC PPN leveraging the information and analysis extracted from the predictive referral model. The proposed model is a two-stage stochastic mixed-integer model considering the uncertainty in the number of available nurses and discharged patients. The study uses Binary first stage algorithm to solve the model and generate the decision-making parameters. The results indicate that PAC PPN could facilitate smooth transitions between care settings increasing access to PAC, which is beneficial for reducing patient cost ensuring continuous quality care.

Effective care coordination between hospital and PAC entities is crucial to ensure the availability of PAC service for its maximum utilization. The proposed PPN model, which involves a contract agreement between ACHs and PACs within a region, would strengthen this care coordination and thus be a powerful strategic approach in improving patient outcomes.

DEDICATION

To My Amazing Husband

Imtiaz Ahmed

To My Dear Parents

Md Kamal Uddin and Jobeda Akter

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Earning a Ph.D. degree has always been a lifelong dream for me. Finally, I passed all the bars successfully and literally one step away from getting it. However, the six years long journey was not easy and from time to time it became as difficult as it could be. It takes no less than blood, tears and sweat to complete a research project worthy of a Ph.D. degree. I would not be able to finish this project if some of the greatest minds with heart of gold were not there to help me out. In this section, I would like to call out their names to express my heartfelt gratitude.

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1.1 Post-acute care (PAC) service and referral: An overview

Post-acute care (PAC) facilities provide treatment for acute-care patients following hospital discharge and are known to improve patient outcomes, readmission rates, mortality, and functional disability [1, 2]. Their usage has grown over 80% since 1996 [3], causing the U.S. Medicare's annual PAC spending to double since 2001 [4]. Medicare spending on PAC for heart attack, congestive heart failure, and hip fracture grew 4.5-8.5% annually from 1994 to 2009, as compared to a growth of 1.5-2% per year for total spending in the U.S. [3]. Recent reports demonstrated PAC to be the largest contributor (40%) to Medicare spending variation among geographic regions [5]. For example, in 2013, Medicare spent one of every six dollars (about $60 billion) on PAC reimbursement [6]. Conditions frequently requiring PAC referral upon acute care discharge include respiratory failure, stroke, joint replacement, cardiac surgery, heart failure, and pneumonia. Services are provided to these patients through various settings, which include long-term acute care hospitals (LTCH, 428 facilities in the U.S.), inpatient rehabilitation facilities (IRF, 1165 in the U.S.), skilled nursing facilities (SNF, 16,000 in U.S.), and Certified Home Health Agencies (HHA, 33,000 in U.S.) [7]. Specific rules and regulations govern admissions to each of these providers. The vast majority of post-acute care is furnished by skilled nursing facilities and home health agencies.

PAC is accounted for approximately 15% of total Medicare related expenditures amounting to more than 2.7 trillion dollars [8]. It plays a vital role in the nation‘s health care sector by providing patients rehabilitation and long-term care services. It ensures the continued recovery process and help patients to recover their health. The current lack of coordination between hospitals and PAC

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providers leads to a system where the hospitals just see the PACs as vendors to whom only referrals can be made, and the PACs provide the referred patients services for a significant fee if available. The two systems work independent from each other and thus contribute to a significant system loss. It is no wonder that the patients become the ultimate sufferers. This culture can be improved by developing a proper care coordination framework. It is worth mentioning that the referral guidelines and protocols are highly variable across geographical regions, populations, and hospital settings and thus make the coordination a very difficult task.

The healthcare practitioners are continuously urging for enhanced coordination between general acute-care hospitals and post-acute providers to improve overall quality of care and reduce total health spending. Following the same urge, the Affordable Care Act has, increased the incentives for acute care systems to work closely with post-acute providers. Both hospitals and PAC providers also started to realize that only their joint, coordinated effort can reduce the overall healthcare costs and ensure patient satisfaction at the same time. This long awaited coordination framework becomes more relevant now more than ever due to some of the current initiatives such as readmission penalties, value-based purchasing, and risk-based payment models such as bundled payments and Accountable Care Organizations (ACOs) [9]. Moreover, hospitals have already taken the first step towards coordination by providing incentives to reduce hospital length of stay which highly aligns with the PAC provider‘s interests.

To effectively oversee and manage patients after hospital discharge, hospitals and post-acute facilities need to work collaboratively forming a network composed of preferred post-acute providers. In order to establish the collaboration, the acute hospitals need to estimate the future post-acute care needs following a standardized referral protocol. Throughout this dissertation, we are going to work with standardizing post-acute care transition approaches and improving the care coordination between acute hospital and post-acute facilities.

1.2 Problem statement

‘Affordability’ is one of the most significant problems of the current United States healthcare continuum [10], and it has transformed the volume-based healthcare economics to a value-based one. Especially, mitigation of hospital readmission is getting priority as a measure of healthcare quality and cost-savings in recent years [11, 12, 13]. Prolonged inpatient length of stay (LOS) is another important contributor to substantial healthcare costs [14, 15, 16]. Therefore, reduction of readmission and optimization of the inpatient hospital stay, without sacrificing quality of treatment is fundamentally important. This goal incentivized the growth of post-acute care (PAC) services, which have promising potentials as they provide treatment to patients following acute care hospital discharge improving their outcomes, readmission rates, mortality, and functional disability [10, 11].

Although PAC services play an essential role, they are heterogeneous, poorly coordinated with acute healthcare systems, and exhibit high regional variation in usage and availability. Also, the PAC referral patterns vary widely, raising concerns about substandard care and inflated costs [11, 14]. To mitigate these issues, hospitals and healthcare systems are forming PAC preferred provider network (PPN) as a partnership between hospitals and PAC providers that focus on facilitating smooth transitions between these care settings and ensure an effective care coordination. Through these networks, hospitals and PAC providers can exchange essential clinical information, care management protocols, and, increasingly, share savings. However, the formation of PAC PPN is complex and requires a clear understanding of referral patterns to PAC providers, PAC financial and quality performance, and PAC providers capacity and ability to serve patients from certain geographies and varying levels of acuity. While forming this network, hospitals will have to carefully manage their downstream post-acute bed capacity to help avoid upstream congestion delays in emergency and surgical departments. Delayed hospital discharges are a major cause of upstream congestion, and these delays often result from bed capacity shortages in the various post-acute care settings [17].

Unfortunately, PAC is, perhaps, the least understood portion of the healthcare continuum, and comparatively little studies were completed on the rational planning and effective use of post-acute services. To develop a rational planning and effective design of the PAC PPN, factors associated with PAC referral decisions at acute care discharge need detailed characterization. It is also essential to have some evidence-based investigation on the effectiveness or influence of PAC service on healthcare quality metrics, i.e., inpatient length of stay (LOS) and readmission, so that appropriate intervention can be planned accordingly. With all these investigations and analysis performed, a pressing need is to build a optimization model for PAC PPN that could provide a strategic and standard approach to generate best possible values for decision making and capacity planning parameters.

1.3 Motivation and scope

Variance in PAC referral practices leads to the belief that standardized referral guidelines would be beneficial from both outcome and cost perspectives [2]. To achieve this target, it is first necessary to understand the prevailing PAC referral practices across the dimensions of geographic region and patient acuity; this would help to identify the cause of variation and estimate the post-acute care needs to facilitate the PAC PPN discharge planning. Then, based on this understanding, a predictive model can be developed to help standardize the referral practice.

Analysis of PAC's effectiveness or quality is also necessary during the standardization procedure. However, it is complex due to high variabilities between patient to patient, procedures to procedure, and PAC types. The relationship of common healthcare metrics and PAC relationship is also ambiguous. Hence, investigation on the intertwined relationship of LOS, readmission, and PAC referral is essential to ensure that patient care is not getting compromised.

In a robust PAC PPN network, the hospital and the PAC providers should agree to a standardized set of policies and procedures that optimize patient care. To conform to the agreement, hospitals and PAC providers both need to adjust their operational planning and plan for resource and capacity adjustment. Typically, hospitals will have to carefully negotiate the right amount of capacity for each type of PAC services in the PPN; too much capacity will lead to inappropriate usage due to supply side effects, while too little will engender delayed hospital discharge and bed-blocking [18, 19]. These decisions are challenging due to the complex nature of patient flow from acute hospital to post-acute settings that comprises of uncertainties of patient arrival, patients' length of stay, availability of service providers and other resources in the system. These uncertainties motivate the need of a stochastic optimization model that would result in 'best' decisions for the operational planning to form a PAC PPN.

1.4 Related works

To develop a PPN for continuous and appropriate care coordination from ACH to PAC settings is challenging. It requires detail understanding of the current practice exist in the healthcare system along with exploration of the recent literature. This section provides a brief literature review in three different perspectives focusing on (1) studies on overall PAC referral and PAC referral for cardiovascular disease (CVD) patients, (2) studies relating the association of LOS, readmission, and PAC for CVD patients, and (3) studies performed or proposed to support PPN formation. Each subsection identifies the gaps in the existing literature and further motivates the need for the proposed research.

In this research, the focus is limited on patients with CABG or VR procedures as these are the two of the most prevalent cases of hospitalization and the leading cause of death in the U.S. and frequently need PAC services [11]. Around 114,028 hospitalizations were reported in 2007 for CABG surgery alone and 137,721 combined surgeries were reported for CABG and VR procedures [13]. Also, being one of the most expensive surgical procedures, CABG and VR are priority domains for hospital outcome development with significant implications on patient morbidity, mortality, and health care spending which are important aspects to consider for the development of a PAC PPN.

1.4.1 Post-acute care referral

The overall practice of using PAC services has increased over the last two decades. However, it is still one of the least researched segments of the U.S. healthcare system to date. In 2007, Heinemann [20] called for establishing evidence-based practice for PAC rehabilitation outcomes. Since then, PAC and healthcare outcomes studies were emphasized, mostly involving stroke patients. Studies on associations between PAC, LOS, and readmission [21, 22] reported positive associations between increased use of PAC, shorter LOS, and lower risk-adjusted readmission rates. Studies specific to PAC referral [22, 23, 24, 25, 26] found that memory and comprehension, living status, and social support are the major determinants of discharge location. Also, reduction of the readmission rate for cases with strong hospital-SNF linkages [27] and high nursing care quality [28] was noticed.

In contrast to stroke, little work was completed addressing the PAC referral for CVD patients, especially those undergoing CABG or VR, accounting for over 500,000 operations annually [29, 30, 31]. One study on CVD patients reported that 56% of such patients were referred for rehabilitation at discharge, with those exhibiting elevation myocardial infarction, comorbidities, and greater age being more likely to be referred [32]. Further, Dolansky et al. [30] presented that race, gender, and LOS are the prominent factors associated with PAC use in case of older cardiac patients. No studies, however, explored predictive modeling for PAC destination following heart surgery, especially CABG and VR, considering hospital characteristics in terms of location, capacity, and other specialties. So, an appropriate predictive model to capture the current practice of PAC referral for CVD patients including hospital characteristics along with patient demographic and diagnosis information could make a significant difference.

1.4.2 Investigation of the association of PAC and healthcare metrics

Readmission and LOS are typically accepted parameters of quality measures for surgical care. Therefore, numerous studies[33, 34, 35, 36, 37] were conducted focusing on the relationship of LOS and readmission; however, the findings are highly case-specific. For example, a Massachusetts study on CABG patients found that readmission rates and patient mortality are held constant when significant reductions in LOS are accompanied by increased PAC usage[34]. Lois et al. [38] also hypothesized that a shorter postoperative hospitalization does not increase the likelihood of readmission. However, according to some research findings [39, 40], a short LOS after hospitalization for Heart Failure was associated with increased rates of cardiovascular and HF readmissions. Apparently, differences in patient conditions, diseases, and other factors result in such differences in results. Therefore, researchers are continuously studying and trying to investigate the relationship between LOS and readmission in different settings, on different patient cohort, and so on.

So far, many researchers [11, 33, 34] worked on CABG patients' connection with readmission and reported the postoperative infection, heart failure, and cardiopulmonary complications as the most common variables. Connerney et al. [41] indicated depression and Murphy et al. [41] postulated absence of a partner resulting in living alone after discharge as vital factors for predicting readmission after CABG. Other studies developed readmission prediction models following heart failure [42, 43, 44]. Significant predictors included the type of valve surgery, hospital LOS, discharge location, age, and the degree of patient follow up. In contrast, studies on LOS [16, 45] reported Body Mass Index, type of surgery, non-elective surgery, current congestive heart failure (CHF), renal failure, and overall the total number of complications as the important factors affecting postoperative LOS. Peterson et al. [14] investigated the effects of hospital variability in LOS after CABG. They found a correlation between postoperative LOS (PLOS) and hospital's risk-adjusted mortality results. Although these are mentionable works on understanding the risk factors of LOS and readmission (independently) for CABG and VR patients, the coupled analysis of both readmission and LOS with the commonly known predictors in terms of health care delivery, demographic status, patient comorbidities, and PAC services are limited. In particular, no investigations directly focused on the interrelation of the risk factors of readmission and LOS with an association of PAC referral for patients following CABG and VR. Thus, identifying some common and interrelated risk factors of readmission that involve LOS decision and PAC referral can help medical practitioners to gather some strategic guidelines while building PPN with PAC facilities.

1.4.3 PAC preferred provider network

Since the last couple of years, medical practitioners and policy makers are urging to create a preferred network of SNFs to collaborate more closely with ACHs with a view to improving the coordination of care of patients requiring such services. The major goals behind such proposition are to improve communication and sharing of information between the SNFs and primary care physicians, to decrease the patient LOS in an SNF (when medically appropriate), and finally, to reduce the number of hospital readmissions.

So far, very few studies are completed on the PPN concept. In [46], the author outlined the internal and market factors that governs health systems' decisions regarding their integration with post-acute providers to develop a preferred network. They emphasized that enhanced integration between acute-care and post-acute providers would reduce the variation in post-acute spending. In [47], the author performed a concurrent mixed-methods approach, combining Medicare claims data with qualitative data gathered from interviews, to investigate the changes in re-hospitalization rates; they also compared the differences in practices between hospitals connected with and without formal SNF networks. Hospitals with formal SNF networks indicated an overall relative reduction of readmission, which was 4.5% higher than the reduction for hospitals without SNF PPN. Interviews revealed that hospitals with networks had expanded their existing relationships with SNFs, effectively managed patient data, and exercised a looser interpretation of patient choice.

Kennedy et al. [48] performed a mixed method study on 366 respondents to the National Survey of Accountable Care Organizations (ACOs). They outlined the common elements of a PPN - care transitions beginning at hospital admission, embedded ACO staff across settings, solutions to support information sharing, and jointly established care protocols. They also reported some important challenges of PPNs, i.e., misaligned incentives, unclear regulations, and the lack of integrated health records. Vasilevskis et al. [47] also supported the idea of joint accountability and collaboration between hospitals and their SNF partners to reduce future readmission.

Konetzka et al. [49] worked on a 2005-2013 dataset on Medicare beneficiaries receiving PAC treatment in the U.S., and examined the integration between hospitals and the two most common PAC settings: SNF and HHA. The study reported that formal integration between hospitals and SNFs increases Medicare payments and reduces readmission. However, it has little impact on HHA cases; so, does the informal integration between hospitals and either PAC setting.

Despite all these efforts and guidelines to establish PAC PPN, no studies, so far, have modeled the patient distribution framework. Also, the factors affecting capacity or resource requirements to a PAC (as a part of the PPN) have not been addressed in literature. These factors are dynamic, multidimensional, and fluctuating by nature. So, deterministic modeling approaches are inadequate, and a stochastic optimization is required to capture the uncertain scenarios of this agreement.

1.4.4 Application of stochastic optimization in healthcare system modeling

Stochastic optimization is a well acclaimed mathematical modeling-based approach for optimization problems that deals with uncertainty. Stochastic optimization has been proved to be much better and more versatile compared to deterministic formulation for solving real life optimization problems. In order to deal with uncertainty in stochastic formulation, the two-stage stochastic program with recourse is used as a popular method. In this special class of stochastic models, the first-stage decisions are made prior to realizing the value of the uncertain parameters. After that, the second-stage decisions are made once the uncertainty in the problem data have been realized. While optimizing the overall objective is to minimize the sum of first-stage costs and the expected value of the random second stage costs which is also termed as recourse costs. Such problems have been developed in extensive applications, e.g., production planning [50], capacity planning and resource acquisition [51, 52], facility location [53], scheduling [54, 55], vehicle routing [56, 57], environmental control[58] and healthcare optimization [59]. Over the last few decades, stochastic optimization technique has been applied in various aspects of healthcare applications[60, 61, 62, 63, 64, 65, 66, 67, 68].

However, the two-stage stochastic programming method becomes a very challenging one when it deals with integer variables known as two-stage stochastic integer programming which integrates discrete optimization problems into the large dimensional stochastic programs. In real world application, it is not very uncommon to have integer variables in optimization problems. Several algorithms and approximation ways have been developed to tackle the challenge of stochastic integer problems. The case of first-stage binary variables is one of those approaches and has been successfully applied to solve a variety of stochastic problems such as plant layout, location and routing, supply chain optimization, capacity planning and capital investment. In order to solve this class of stochastic problems, Laporte and Louveaux [69] developed an integer L-shaped method for problems with binary first-stage variables and arbitrary second-stage variables. Their method extends earlier work [70] for two-stage stochastic linear programming with 0-1 integer first-stage variables. This dissertation also proposes a two-stage stochastic model to develop the PAC PPN where the first stage includes binary variables, and the second stage includes both integer and continuous variables.

1.5 Organization of this dissertation

The dissertation works on establishing a proper care coordination from Acute Care Hospitals (ACH) to PAC settings developing a framework for PAC PPN. In particular, this work will help to (1) understand the prevailing PAC referral pattern and variation of PAC use with assessment of the factors influencing these variations, (2) investigate the common and interrelated risk factors of LOS decision and readmission risk with PAC referral, and (3) support strategic contract agreement decisions and resource adjustment planning to form a PAC PPN. Eventually, these activities will deliver the groundwork to develop a PAC capacity profile that best meets the need of evolving post-acute demands through an appropriate PPN-based care coordination.

The rest of this dissertation is organized as follows: Section 2 develops a predictive analytical model to determine discharge locations (PAC setting) for patients after acute hospitalization. Section 3 develops two predictive analytical models to estimate the LOS and risk of readmission of acute care patients. These models are developed mainly to investigate the interrelated relationships of LOS and readmission risk factors and summarize some significant findings. Section 4 proposes and solves a mathematical framework to build the PAC PPN using stochastic optimization model, namely two-stage stochastic Mixed Integer Problem (MIP). This model will help obtain the strategic decision values required to establish a formal partnership between acute hospitals and PAC providers. However, the outcome and decisions should vary depending on class and nature of patients and patients' PAC service requirement. Since cardiac artery bypass graft (CABG) and valve replacement (VR) patients exhibit increased risks of additional cardiac events, PAC rehabilitation is essential for restoring quality of life and mitigating mortality risk [71, 32] , and therefore, make an excellent case for this PAC focused study. Therefore, patients, who had gone through CABG or VR as their index hospitalization procedures, were considered as the sample cohort for this proposed research. Finally, section 5 summarizes the potential contribution along with the overall impact of this research and highlights potential extensions beyond this dissertation.

2. POST-ACUTE CARE REFERRAL: A COHORT STUDY OF PATIENTS WITH CORONARY ARTERY BYPASS GRAFT OR VALVE REPLACEMENT*

2.1 Introduction

The use of post-acute care (PAC) for cardiovascular conditions is highly variable across geographical regions. Although PAC benefits include lower readmission rates, better clinical outcomes, and lower mortality, referral patterns vary widely, raising concerns about substandard care and inflated costs. One of the prime objectives of this work is to examine the geographic variations in PAC referral pattern and identify the associated risk factors related to hospital characteristics, patient demographics, and clinical information for the decision of discharge location for CABG and VR. To accomplish the objective, patient-level detailed cohort data was obtained through an electronic health record system, and the association of the risk factors influencing PAC as a discharge destination was quantified. In the first work, the existing PAC referral pattern in the U.S. acute care hospitals were studied and factors associated with variation in the referral practice were assessed. A predictive model was developed, which would be beneficial in terms of providing discharge planning information early in the patient's acute care stay and thus, could strongly facilitate discharge processes, care coordination, and transition of care following surgery. In the following subsections, data cleaning, methodologies, and results from this work are discussed in detail.

2.2 Study data

For this research study, data was extracted from the Cerner Health Facts data warehouse, shared by the Oklahoma State University Center for Health System Innovation (OSU-CHSI). The Cerner

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data contains information about 63 million unique patients over a span of 16 years from more than 850 USA facilities, and as such serves as a good representative sample of the U.S. patient population. The data was de-identified and did not contain any personally identifiable information. Data extracted for this study spanned between January 2010 to December 2015 and was reviewed and approved as an exempt study by the Institutional Review Board of Texas A&M University.

The study population consisted of patients who had CABG or valve replacement (n= 14,224) surgery. International Classification of Diseases, 9th Clinical Modification (ICD-9-CM) procedure codes (10 codes) [36.10-36.17, 36.19-36.2] were used to identify the CABG patients and (21 codes) [35.00-35.04, 35.10-35.14, 35.20-35.38, 35.97, 35.99] were used to identify patients with valve replacement. In case a patient had multiple hospitalizations for the same condition in the study window, only the first admission was included to avoid potential effects of aging or readmission.

This study only included adult patients ($\geq$ 20 years) admitted through the emergency department or transferred from other clinical facilities or referred by a physician/HMO. Among these patients, who were discharged alive after their index hospitalization, were considered. Patients who expired (n=185), left against medical advice, and discharged for outpatient service (considered as inappropriate discharge location) were excluded from the study. Patients who had procedures performed before the admission date or after the discharge date (considered as incoherent data) were also excluded. This study also excluded patients with length of stay $>$ 75 days and with missing predictor variables (n=2,685). All these exclusions resulted in a final sample size of 14,224 patients from 49 acute care hospitals. Fig. 2.1 summarizes the data cleaning and study cohort generation process.

2.3 Variables considered

In this work, discharge destination was considered as dependent variable which was obtained from the initial encounter table. The categories of discharge destination were: (1) Discharged to home, (2) Discharged to home health care service (HHC) (3) Discharged to skilled nursing facility (SNF)

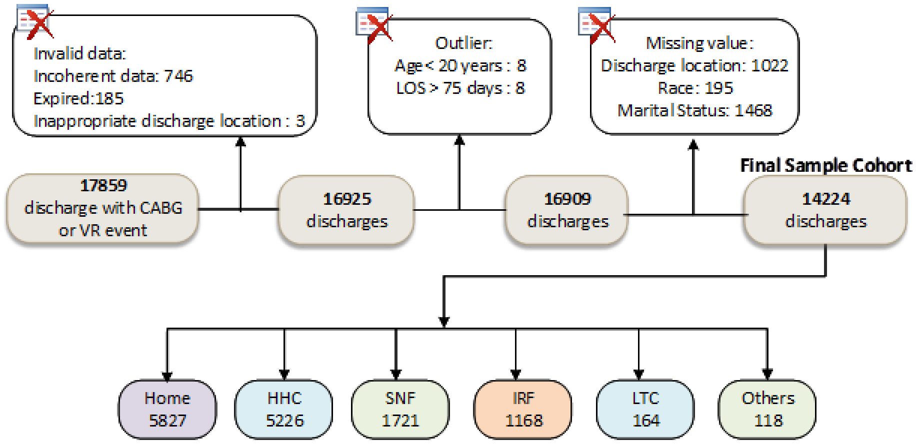


Figure 2.1: Flow diagram of the final sample cohort processing through data analysis.

(4) Discharged to long term care hospitals (LTCH) (5) Discharged to inpatient Rehabilitation facility (IRF) (6) Discharged to others. Discharged to 'others' included several miscellaneous discharge locations, and the number of patients discharged to these locations was very low. The miscellaneous locations were discharged to another short-term hospital, discharged within this institution to Medicare-approved swing bed, discharged to court/ law enforcement/jail, discharged to a designated cancer center or children's hospital, discharged to a federal health care facility, discharged to a psychiatric hospital, and unknown. All of these miscellaneous locations are binned into one category 'others' to bring clarity in our analytical model.

In the analytical model, in total, 29 independent variables were considered. The independent variables were categorized into five categories like hospital location (census region), provider/hospital characteristics, patient demographics, related factors of PAC referral discharge, and comorbidity and diagnosis information. Table 2.1 provides a list of the 29 variables considered in this study.

This study considered census division of the hospital in the regional (hospital location) category and hospital bed size range, the teaching facility affiliation, and Hospital status (urban or rural) are categorized under provider/hospital characteristics. Demographic variables include age, marital status (married, divorced, single and widowed), race (Caucasian, African American, Asian, Hispanic, Native American and others), gender. Other predictor variables related to PAC referral discharge were the length of stay and the Charlson Index. The length of stay in the hospital was identified by the number of hospital days. Based on the frequencies of the CABG and VR procedures in the study population, four CABG procedures and two VR procedures are identified, accounting for approximately 90.9% (12935) patients' reasons for hospitalization. These include coronary bypass surgery for two arteries (n=4496), coronary bypass surgery for three arteries (n=3133), coronary bypass surgery for one artery (n=2743), coronary bypass surgery for four or more arteries (n=1108), open and other replacement of aortic valve with tissue graft (n=874), and open and other replacement of aortic valve (n=581). These six events were considered as independent binary variables to facilitate examination of the effect of these specific cardiac procedures in the discharge decision.

Comorbidity is defined as the coexistence of additional diseases or disorders in the same person with a specific index disease [72]. To assess the contribution of comorbid conditions in the discharge location (PAC referral), it was examined if the patient had suffered from atrial fibrillation (ICD9-427.31), hypertension (ICD9-401.9), coronary atherosclerosis (ICD9-414.01), intermediate coronary syndrome (ICD9-411.1), hyperlipidemia (ICD9-272.4), acute posthemorrhagic anemia (ICD9-285.1), acute myocardial infarction (ICD9-410.71), tobacco use disorder (ICD9-305.1), diabetes mellitus without complication (ICD9-250), acute kidney failure (ICD9-584.9), pulmonary collapse (ICD9-518), congestive heart failure (ICD9-428) and unspecified anemia (ICD9-285.9). These thirteen comorbid diagnoses were selected for assessment because they were the most frequent common comorbidities in the study population. However, the Charlson comorbidity index was used to capture the overall effect of comorbidities in each patient [15].

Table 2.1: Variables considered for the discharge location predictive model

Category	Predictor Variables
Regional (Hospital Location)	Census division
Provider/Hospital	Bed Size Range
	Teaching Facility Affiliation
	Hospital Status
Patient Demographic	Race
	Gender
	Age
	Marital Status
Related factors of PAC referral discharge	Length of Stay
	Charlson Index
Comorbidity and Diagnosis information	Coronary Bypass of One Coronary Artery
	Coronary Bypass of Two Coronary Arteries
	Coronary Bypass of Three Coronary Arteries
	Coronary Bypass of Four or More Coronary Arteries
	Open Aortic Valve Replacement Tissue Graft
	Open Aortic Valve replacement
	Diabetes Mellitus without complications
	Tobacco Use disorder
	Atrial Fibrillation
	Unspecified Hypertension
	Coronary Atherosclerosis
	Intermediate Coronary Syndrome
	Hyperlipidemia
	Posthemorrhagic Anemia
	Acute Myocardial Infarction
	Congestive Heart Failure
	Anemia, Unspecified
	Pulmonary Collapse
	Acute Kidney Failure, Unspecified

2.4 Methods and results

2.4.1 Descriptive analysis and model development

The primary focus of this study is the analysis of patient discharge location (PAC referral). Analyses included descriptive statistics for discharge location (Fig. 2.2) and exploratory analysis (univariate and bivariate analyses). Variables with large numbers of missing values and outliers were excluded. Chi-square tests were performed for categorical variables to test for differences in distribution of discharge locations among patients. Variables with p-value less than 0.1 [73] in the bivariate test were included as candidates in the multinomial logistic regression model. Percentages and medians with interquartile ranges are recorded for categorical and continuous variables in Table A1 (appendix). The likelihood ratios for all variables are also reported in Table A1.

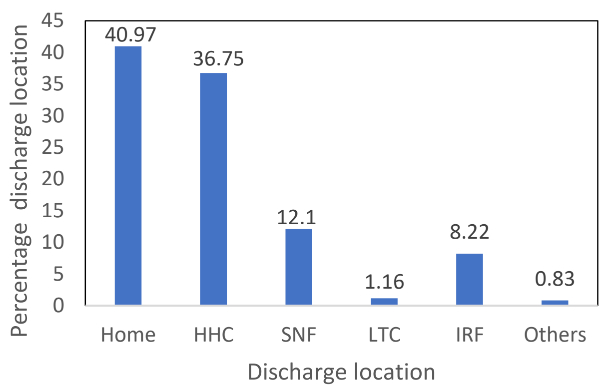


Figure 2.2: Distribution of discharge location.

Regression analysis has been widely used in healthcare and medical research in different predictive models specially in the field of disease prediction, patient outcome prediction (i.e. readmission, mortality) and so on. Multinomial logistic regression is a popular method used for predicting a response variable with more than two categories (i.e. Home, LTCH, SNF, IRF, HHC) .

In this study, multinomial logistic regression was used to develop the analytical model, and 'Home' was used as the reference category. 'Home' was selected as the reference category because this category represented the highest percentage (40.96%) of the discharge destinations. To reduce bias in estimation of such analytical models, the clustering effect of patients within facilities within geographic regions is emphasized to consider performing multilevel mixed model [74, 75]. Therefore, multilevel analysis approach considering random effects from the census division was tested and found that the difference between single and multilevel results is negligible. For example, the difference between single and multilevel model misclassification errors is 0.21% only. Also, the Akaike Information Criterion (AIC) difference between two models is 0.417%. It implies that there is none or minimal clustering effect of census divisions in our dataset. So, a single-level analysis approach was considered in this work. The model's accuracy was calculated based on multiclass receiver operating characteristic (ROC) value and overall misclassification error. A 10-fold cross-validation of the model was conducted to assess model overfitting. The mean misclassification error of cross-validation was contrasted with the misclassification error of the model developed with the entire cohort. A flowchart describing the methodology used to develop and validate the model is shown in Fig. 2.3.

The relative risk ratio (RR), the p-value, and the 95% likelihood confidence intervals of the predictor variables for each category are reported in Table A2 (see appendix section). The data analysis and all the statistical tests were carried out in R version 3.2.3, an open-source package from the R Foundation for Statistical Computing [76].

2.4.2 Results

2.4.2.1 Model interpretation

The final cohort of the study population had a mean age of 63.5 ± 11.81 years (mean $\pm$ sd) with 10,234 (71.9%) male and 11,946 (84%) Caucasian. Fig. 2.2 describes the distribution of the

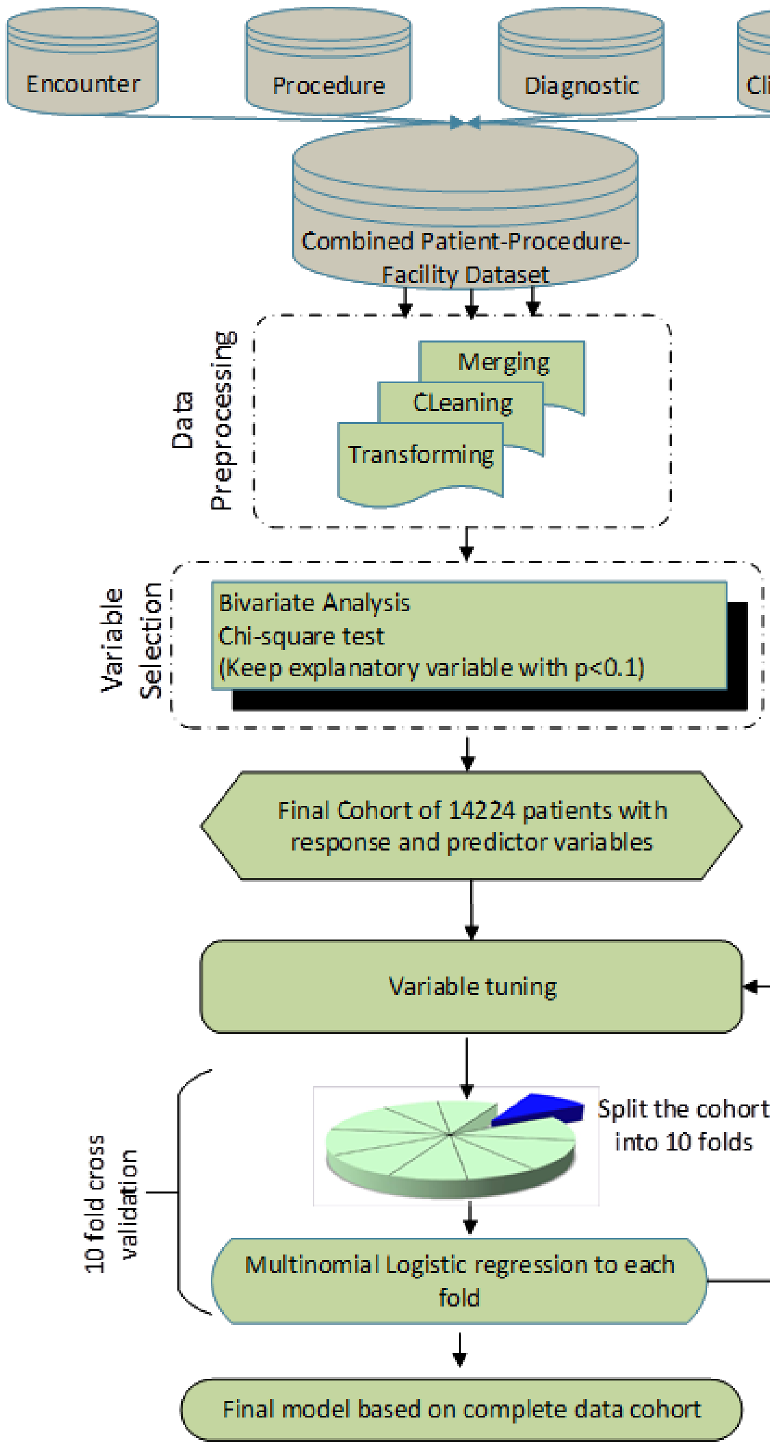


Figure 2.3: Flowchart of the methodology followed to develop the predictive model.

discharge destination. The most dominant discharge location was Home (40.97%), followed by HHC (36.75%), SNF (12.10%), IRF (8.2%), and LTCH (1.16%). Table A1 (in appendix) summarizes demographic characteristics, hospital information, and information related to cardiac events and comorbidities for each discharge location. Discharge location 'others' does not represent any specific PAC type. Therefore, in the rest of the result section, discharge location category 'others' is ignored while discussing the model insights.

2.4.2.2 Factors related to discharge destination selection

Table A2 (in appendix) provides the significance of the factors associated with discharge destination in the multinomial logistic regression. A p-value of 0.05 was used as a threshold to distinguish significant variables. The relative risk ratio and 95% confidence interval (CI) limits are also provided. The association of the factors related to discharge location is stated in the following paragraphs.

(i) **Regional (Hospital Location)**:

The location of the hospital, captured as census division, was found to be strongly associated with the selection of discharge location. For census division, 'East South Central' was chosen as the reference category. Patients in West South Central are around 13 times more likely to discharge to LTCH, 9 times more likely to HHC, and 3 times more likely to SNF or IRF compared to patients in East South Central. Patients from the Middle Atlantic are around 6 times more likely to discharge to HHC, 3 times to SNF, 2 times to IRF, and 2 times to LTCH compared to home than patients from East South Central. Fig. 2.4 summarizes the risk ratios for the nine census divisions.

(ii) **Provider/Hospital**: The bed size of the index hospital was also found to be a significant predictor of discharge destination. The bed size range of 500+ was chosen as the reference category in the model. Compared to the 500+ bed size hospitals, those with 300-499 bed size are 40% and 70 % less likely to discharge patients to SNF and HHC, respectively, and around 3 times more likely to discharge to IRF compared to Home (Table A2). Patients from

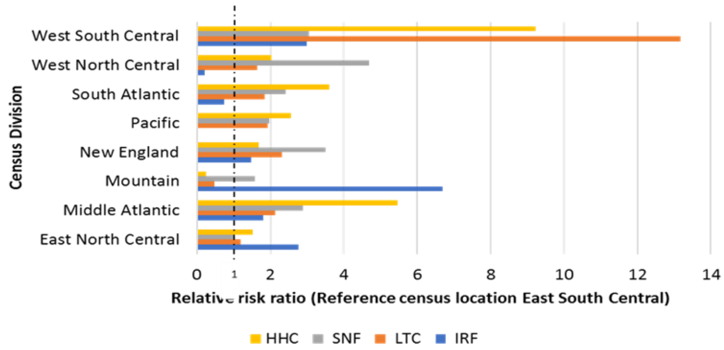


Figure 2.4: The relative risk ratio of 9 census divisions for 4 types of PAC.

200-299 bed size range hospitals are 50%, 70%, and 50% less likely to discharge to SNF, HHC, and IRF, respectively, compared to Home. Patients admitted to hospitals with bed size range 6-99 are less likely to be discharged to HHC and LTCH. Fig. 2.5 summarizes the variation of the RR values for different bed size range.

Whether a facility is a teaching hospital or not was also a significant factor of discharge destination. Hospitals with teaching are less likely to discharge patients to PAC compared to home. No significant difference was found in referral to HHC, IRF, and LTCH between urban and rural hospitals.

(iii) **Patient Demographic**: Gender was found to be significant for discharge location. Females are more likely to be discharged to PAC than males. The likelihood of a female patient being discharged to SNF and LTCH is twice that of males. Further, Asians are around two times more likely to be referred to HHC compared to Caucasians, and single, divorced, and widowed patients are 2 to 3 times more likely to be discharged to SNF, IRF, and LTCH compared to married. Age is another significant predictor in the discharge destination referral, with the likelihood of PAC referral increasing with age.

(iv) **Related factors of PAC referral discharge**: Length of stay and Charlson comorbidity index were also significant predictor variables for the decision of discharge location. Patients with

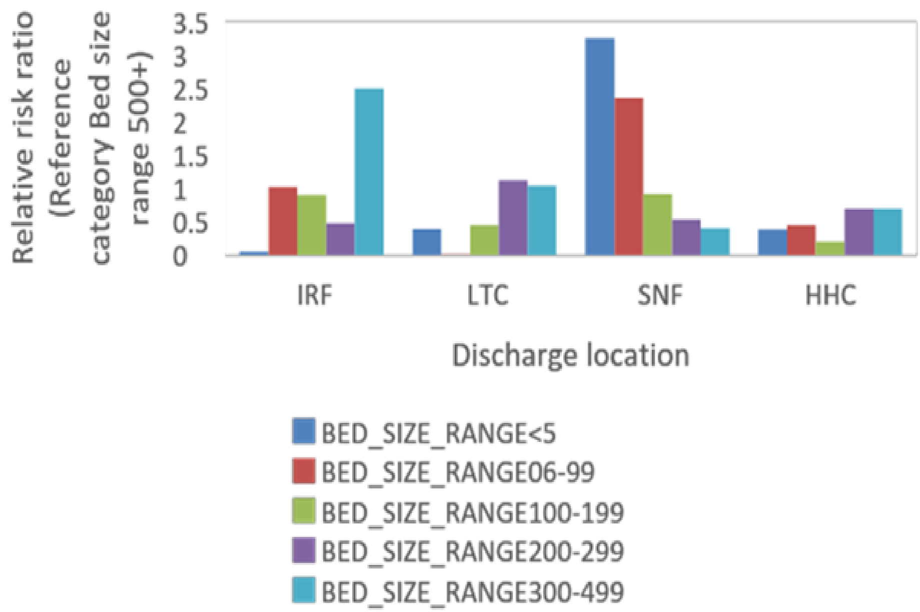


Figure 2.5: The relative risk ratio of different bed size range for 4 types of PAC.

longer length of stay and higher comorbidity index were more likely to be released to a PAC facility compared to Home.

(v) **Comorbidity and Diagnosis information** : Patients with valve replacement exhibited higher discharge rates to PAC facilities compared to non-valve replacement. CABG and VR patients diagnosed with coronary atherosclerosis and tobacco use disorder are less likely to discharge to a PAC facility compared to Home. However, CABG or VR Patients diagnosed with acute kidney failure are 2 times more likely to discharge to LTCH. The associations of other individual comorbid diagnoses were not found to be significant.

2.4.2.3 Predictive power of the model

The average 10-fold cross-validated predictive accuracy of the model is 62.6% considering overall misclassification error. The average cross-validation (CV) accuracy (62.5%) is consistent with the accuracy based on the complete cohort. The standard deviation of the accuracy based on CV is very low (0.015) indicating that model is very stable to data/sample variations. The misclassification error in each of the CV runs did not differ significantly from the findings in the complete cohort. Fig. 2.6 shows the multiclass ROC curves for every discharge location category along with overall ROC for the model. pROC package from R was used to analyze and compare the multiclass ROC curves for 6 discharge locations [77]. The area under the overall ROC curve (AUC) is 0.685, and the AUC for Home, IRF, LTCH, SNF, HHC, and others are 0.72, 0.53, 0.52, 0.58, 0.72, and 0.46, respectively.

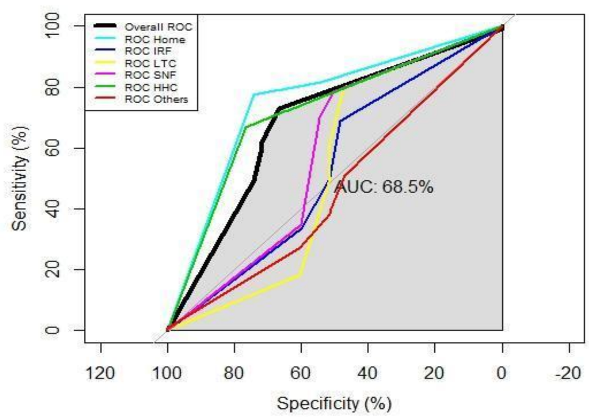


Figure 2.6: Receiver operating characteristics (ROC) curve for multiclass prediction model with multinomial logistic regression.

2.5 Findings

This study revealed that 54.5% of CABG patients and 73.3% VR patients were discharged with some PAC care. This finding seems reasonable because VR procedures are associated with more complexity than CABG. VR patients experience frequent complications after surgery that result in arrhythmias and unspecified heart failure [30]. For those receiving PAC, most were referred to HHC (relative proportion 63.1%), which is consistent with Dolansky et al. [30], who stated that surgery patients require less recovery care than non-surgical medical patients requiring lesser need for PAC. In our study population, IRF and LTCH were infrequently used as only 9.4% patients were sent to IRF and LTCH combined. This is also reasonable for the CABG or VR patients as they typically require little daily physical or occupational therapy (> 3 hours) [30], which is a necessary admission criterion to discharge to IRF. Further, the average length of stay in our study population was 10 days, which does not meet the admission criteria of LTCH (more than 25 days for LTCH admission [78]).

Geographic variation of PAC use was significant, which is consistent with the existing literature [79, 80]. Picone et al. [81] hypothesized that the rate of PAC referral for cardiac patients aged 65 or more is positively correlated with the number of PAC facilities per 10,000 people, which our results partially support. Compared to other divisions (see Table 2.2), West South-Central exhibits higher relative capacity for both LTCH and HHC compared to the mean (LTCH: 2.27% vs 1.45%, HHC: 57.1% vs 37.83%) and higher relative referral to LTCH and HHC compared to the mean (LTCH: 1.80% vs 1.09%, HHC: 45.8% vs 31.59%). Similarly, West North Central exhibits both higher relative SNF capacity and relative SNF referral (69.73% vs 56.39%, 20.4% vs 14.36%, respectively).

However, this capacity effect does not always hold. For example, patients in the East North Central are more likely to be referred to IRF as compared to other divisions (12.2% vs 6.72%), even though the relative capacity is lower than average (3.87% vs 4.32%). Further, among divisions, Mountain exhibits high relative HHC capacity (45.29% vs 37.83%) with low relative HHC referral (2.5% vs 31.59%). For capacity and referral profiles within divisions, Middle Atlantic exhibits high SNF capacity (67.69%) with low SNF referral (16.00%) and low HHC capacity (24.78%) with high HHC referral (68.3%). Overall, these results strongly indicate that, while PAC capacities are sometimes positively associated with PAC referral, other significant underlying factors exist that may contravene the capacity effect. Although researchers conjecture causes such as practice styles, service quality, insurance coverage, and acute/PAC business relationships [80] for these underlying factors, geographic variation in PAC referral is not yet clearly understood.

Table 2.2: PAC capacity and referral rate across census divisions

Census Divisions	Number of PAC Facilities (Percentage within Division)				Referral Percentage within Division				
	HHC	SNF	IRF	LTCH	HHC	SNF	IRF	LTCH	Home
East North Central	2486 (42.40)	3081 (52.55)	227 (3.37)	69 (1.18)	31.2	14.3	12.2	1	41.3
East South Central	443 (27.65)	1043 (65.11)	82 (5.12)	34 (2.12)	13.4	5.7	9.4	1.6	69.9
Middle Atlantic	619 (24.78)	1691 (67.69)	158 (6.33)	30 (1.20)	68.3	16	4.5	0.5	10.7
Mountain	765 (45.29)	794 (47.01)	99 (5.86)	31 (1.84)	2.5	17.3	1.9	0.3	78
New England	442 (30.84)	937 (65.39)	35 (2.44)	19 (1.33)	43.6	20.1	11.2	1.1	24
Pacific	1464 (45.26)	1630 (50.39)	117 (3.62)	24 (0.74)	27.3	21.2	0	1.2	50.3
South Atlantic	1842 (41.37)	2367 (53.17)	176 (3.95)	67 (1.50)	21	9.1	9.9	1.3	58.7
West North Central	770 (25.81)	2080 (69.73)	106 (3.55)	27 (0.91)	31.2	20.4	1.7	1	45.7
West South Central	3173 (57.1)	2026 (36.46)	232 (4.17)	126 (2.27)	45.8	5.1	9.7	1.8	37.6
Mean	37.83	56.39	4.32	1.45	31.59	14.36	6.72	1.09	46.24

The findings suggest that hospital characteristics also affect PAC referrals significantly. Smaller hospitals are more likely to refer patients to SNF (Table A2 Referent 500 beds: bed size < 5, 6-99: SNF RR ratios: 3.2, 2.3, respectively), while larger hospitals are more likely to refer to HHC (Table A2: bed size < 5, 6-99: HHC RR ratios; 0.4, 0.5, respectively). Teaching hospitals are less likely to refer to PAC across all PAC types (Table 2.3 Referent Non-Teaching: Teaching Hospital: SNF RR: 0.2; HHC RR: 0.4; IRF RR: 0.4; LTCH RR: 0.1).

Length of stay and comorbidity are both correlated with PAC referral, which is consistent with past findings [80, 81, 82]. Hospital length of stay is important because early discharge can contribute to less control over the patient's condition and more reliance on PAC use [80]. This study indicates that total comorbidity (Charlson Index) is a better predictor than specific comorbid conditions. This means that overall health complexity has more influence on referral than individual comorbid conditions. As comorbidity increases, the patient is more likely to be referred to SNF, IRF, or LTCH than to HHC (Table A2 Charlson: HHC RR 1.1; SNF RR 1.3; IRF RR 1.3; LTCH RR 1.3). This is consistent with studies on PAC referral for patients with stroke and hip replacement [81, 82]. However, tobacco users or patients with a smoking history are less likely to be referred to PAC, which contradicts the results reported by Brown et al. [32]. The analysis also indicated that CABG and VR patients with coronary atherosclerosis are less likely to be discharged to the PAC facilities (SNF, IRF, LTCH).

Female patients are more likely to be referred to PAC than are males (Table A2 Referent Male: RR >1 for all PAC categories, SNF RR 2.0), which is consistent with Suaya et al. [83], and older patients are more likely to be referred to PAC than younger (Table 2.3 Age: RR >1 for all PAC categories, SNF RR 1.1). These results are consistent with the cardiac study of Dolansky et al. [30], but again contradict the findings of Brown et al. [32], who finds that younger cardiac patients are more likely to be referred to PAC (Age Referent < 50: 66-80 Odds Ratio (OR) 0.9; > 80 OR 0.7). Note that, although the average ages of our dataset and Brown's are very similar, Brown et al. considers not only CABG and VR, but also myocardial infarction, percutaneous coronary intervention (PCI), stable angina, and heart transplant, which could account for these differences.

Race also influences PAC referral, with Caucasians being more likely to use SNF (Table A2 SNF Referent Caucasian: Asian RR 0.4; Native American RR 0.2; Hispanic RR 0.9; African American RR 0.9); Asians and African Americans being more likely to use HHC (Table 2.3 HHC: Asian RR 1.6; African American RR 1.2); and African Americans and Hispanics being more likely to use LTCH (Table A2 LTCH: African American RR 1.6; Hispanic RR 1.2). These results are generally consistent with the review of Cortes and Arthur [84], although they do not consider multiple categories of PAC. Explanations for these racial disparities in the referral practice include cultural practices, education, and language [85]. However, similar demographics-driven disparities are also observed in cardiac rehabilitation practice in Canada. Studies on cardiac rehabilitation referral on using Canadian dataset [86] also reported women, ethnocultural minorities and people with low income to be less referred for cardiac rehabilitation despite their higher needs.

2.6 Summary

In this study, factors linked to PAC referral following acute care discharge was investigated using an EHR-extracted CABG and VR patient dataset. Our findings concluded that the regional location of the hospitals and hospital capacity (bed size) influenced the patient discharge practice. Disparities in PAC availability vis-a-vis referral across different U.S. census regions were also observed. The racial and gender-based disparity was also statistically significant, with Asians, Hispanics, and Native Americans being less likely to be referred to PAC compared to Caucasians, and female patients being more likely to be referred than males. Though patients diagnosed with relevant comorbid conditions were, in most cases, likely to be discharged to PAC facilities after the CABG or VR procedure, tobacco disorder and coronary atherosclerosis patients were less likely to be referred to PAC. These findings can help the clinicians to streamline the discharge planning process early in the patient's acute care stay, and thereby, facilitate discharge processes, care coordination, and transition of care, following surgery.

3. ASSOCIATIONS BETWEEN HOSPITAL READMISSION AND LENGTH-OF-STAY AND POST-ACUTE REFERRAL FOLLOWING CORONARY ARTERY BYPASS GRAFT OR VALVE REPLACEMENT

3.1 Introduction

Prolonged hospital stay and readmission contribute to substantial healthcare cost. Hence, an assessment of the optimal inpatient length of stay (LOS) associated with lower readmission rate is important for healthcare providers. Post-acute care (PAC) facilities have promising potential to shorten the LOS; however, currently their influence on overall patient outcomes is not well understood. The primary goal of this study is to highlight the interrelated risk factors of LOS and readmission for cardiac patients. The study also examines the influence of PAC referral on LOS and readmission. Inclusion of PAC usage in investigating LOS and readmission is considered for two reasons: (i) the substantial growth of PAC usage with a decrease of LOS in acute care hospital over the past two decades and (ii) limited research on PAC facilities' effectiveness on patient outcomes (e.g. readmission) [5]. The main intent of this work was to identify the common and interrelated risk factors for readmission and LOS, so that effective interventions can be planned to reduce healthcare costs and improve patient outcomes.

3.2 Study data

This study is also a retrospective cohort-based study using the same electronic health records (EHRs) data extracted from the Cerner HealthFacts data warehouse that was used in my prior work. This dissertation uses the same dataset for the work 1 and work 2 and therefore, the data cleaning and exploration process are not mentioned in this section to avoid repetition of similar description.

3.3 Variables considered

3.3.1 Dependent variables

In this work, two independent predictive models were developed for LOS and readmission. Hence, there are two dependent variables for two models: (i) LOS, indicates the inpatient hospital length of stay after index hospitalization due to CABG or VR event, and (ii) readmission, specifies the re-hospitalization event of a patient within a specified time interval after initial discharge. The LOS was a categorical variable characterized as: short hospital stay (LOS <7 days), moderate hospital stay (LOS: 7-15 days), and prolonged hospital stay (LOS >15 days). The readmission was considered as a binary variable representing all-cause re-hospitalization within 30 days after the initial discharge.

3.3.2 Independent variables

The independent variables used in this work are mostly same independent variables described in work 1. The independent variables were grouped into healthcare delivery and practice, patient demographics, procedure and diagnosis, and PAC service. The underlying models developed in this work are graphically illustrated in Fig. 3.1.

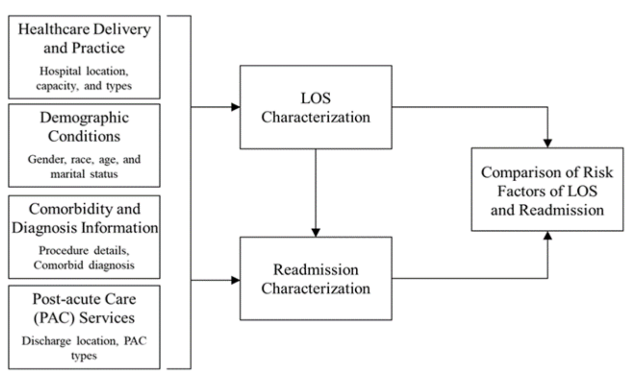


Figure 3.1: Graphical representation of the model development process.

Table 3.1: Predictor variables for the prediction of 30-day readmission and LOS

Category	Predictor Variables
Health Care Delivery and Practice	Bed Size Range
	Teaching Facility Affiliation
	Hospital Status
Demographic Conditions	Race
	Gender
	Age
	Marital Status
Related factors of PAC referral discharge	Length of Stay
	Charlson Index
Comorbidity and Diagnosis information	Charlson Index
	Length of Stay
	Coronary Bypass of One Coronary Artery
	Coronary Bypass of Two Coronary Arteries
	Coronary Bypass of Three Coronary Arteries
	Coronary Bypass of Four or More Coronary Arteries
	Open Aortic Valve Replacement Tissue Graft
	Open Aortic Valve replacement
	Diabetes Mellitus without complications
	Tobacco Use disorder
	Atrial Fibrillation
	Unspecified Hypertension
	Coronary Atherosclerosis
	Intermediate Coronary Syndrome
	Hyperlipidemia
	Acute Posthemorrhagic Anemia
	Acute Myocardial Infarction
	Unexpected Heart Failure
PAC services	Discharge Location

In this study, PAC service was estimated from the discharge location. The categories of discharge locations analyzed were home, home health care service (HHC), skilled nursing facility (SNF), long-term care (LTC), and Inpatient Rehabilitation (IRF). So, the types of PAC service covered was HHC, SNF, IRF, and LTC. Although LOS is modeled as a dependent variable for the LOS model, it was also included as an independent variable in the readmission model to study the effect of LOS on readmission. Table 3.1 provides a complete list of the predictor variables where the first column indicates the category of the variable.

3.4 Methods and results

3.4.1 Methods

A generalized linear mixed model and multinomial logistic regression model were developed to evaluate the readmission and LOS associative risk factors respectively. Referral to PAC was included as a vital predictor in both models to examine its impact on optimal LOS and improving patient outcomes. Analyses included descriptive statistics for all variables associated with the LOS and readmission within 30 days which is presented in Table A3 (in Appendix). Outliers and variables with large numbers of missing values were identified and excluded. A univariate screening was conducted applying Chi-square test and t-test for the categorical and continuous variables, respectively. These assessments indicated the significant differences in the distribution of hospital length of stay, and between readmitted and non-readmitted categories (in appendix Table A3). Percentages and medians with interquartile ranges were recorded for categorical and continuous variables respectively as shown in appendix Table A3. Likelihood ratios for all variables were also reported.

A generalized linear mixed logistic regression was developed with readmission as response and all independent variables were considered as fixed effects except the hospital ID which was considered as random effect. The motivation behind randomizing the hospital ID parameter is that patients' data collected from the same hospital are often correlated and training the regression model using these clustered data might induce additional prediction errors in the regression model [87].Two measures of predictive accuracy are reported, one is the area under the curve (AUC) or C statistic value and another one is the misclassification error generated from the model's estimation outcome.

Multinomial logistic regression, a popular method for predicting a response variable with more than two categories, was used in this study to develop the LOS predictive model. Short LOS represented the highest percentage (43.9%) of patients' inpatient hospital stay, and was used as the reference category. The LOS model's predictive accuracy is reported indicating the multiclass receiver operating characteristic (ROC) value and the overall misclassification error.

The odds ratio (OR), relative risk ratio (RR), the p-value, and the 95% likelihood confidence intervals of the independent variables for both LOS and readmission models are reported in Table A4 (in Appendix). The data analysis and all the statistical tests were carried out in R studio version 3.2.3. [76].

3.4.2 Results

The final cohort of the study population had a mean age of 63.5 ± 11.81 years (mean $\pm$ standard deviation) with 10,065 (71.9%) male and 11,728 (84%) Caucasian. The final cohort consists of 13,982 patients, with 43.8% patients being discharged after a short hospital stay, 43.1% after a moderate hospital stay, and 13.1% after a prolonged hospital stay. Table A3 (in Appendix) summarizes the demographic characteristics, clinical preoperative information, hospital information, and information related to cardiac events and comorbidities for each LOS category and for readmission. Discrete variables were presented as percentage whereas the numerical variables were reported as (mean + SD) or mean [Interquartile range]. Risk models are developed to predict readmission within 30 days and inpatient LOS using the available hospital and patients' clinical and demographic information along with PAC referral details.

3.4.2.1 Factors related to readmission and LOS

The results from two models indicated strong association between hospital location and LOS but moderate association with the readmission. Other factors, which were important for LOS but not readmission, include hospital size, teaching facility status and urban-rural status for acute hospitals. Discharge location or more precisely PAC referral was identified as an important factor to LOS, whereas it does not influence readmission with enough statistical evidence.

Gender and race were determined as highly important factors for both readmission and LOS. Marital status had no significant influence on LOS; however, it affected the readmission considerably. Comorbid conditions showed a significant positive association with both LOS and readmission. Patients with longer LOS and higher comorbidity index were more likely to be readmitted within 30 days after their initial discharge.

The hospital readmission and inpatient LOS models were developed using 28 independent variables (factors). Among those, Fig. 3.2 illustrates a comparative representation of 16 important risk factors associated with LOS and readmission. The outermost radial position indicates the highly significant factors with a p-value less than equal to 0.001. A p-value greater than 0.05 indicates statistically insignificant factors (innermost radial position). For example, gender, as a demographic factor, highly influences LOS whereas it affects readmission moderately.

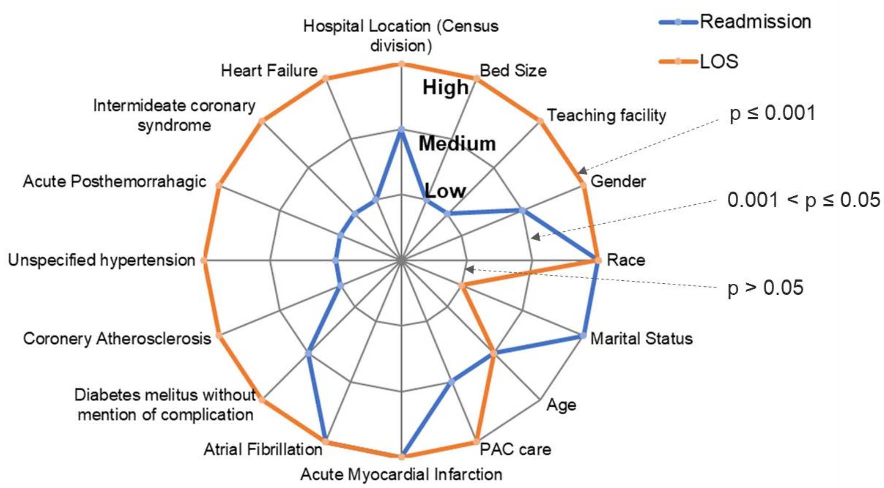


Figure 3.2: Risk factors comparison for readmission and prolonged LOS (based on p-values).

3.4.2.2 Power of the model

The accuracy of the 30-day readmission model was 64%; Area under the Curve (C statistic value) was 0.68, which is consistent with existing literature [36, 88].The accuracy of the LOS model was 63% with multiclass Area under the Curve value of 0.76. An R package named pROC package was used to analyze and compare the multiclass ROC curves for the three LOS categories [77]. The area under the overall ROC curve (AUC) was 0.76, and the AUC for short, moderate and prolonged LOS were 0.81, 0.65, and 0.81, respectively. While developing the model the cohort was divided into two parts. First one was the training cohort (with 80% data) which was used to develop the trained model and the second was the validation cohort (with 20% data) that was used to test the prediction model. The trained model was applied to validation cohort to assess performance on the withheld test data. The performance of the model on the validation cohort (62.9% with AUC 0.745) was very similar to performance on the training data.

3.4.3 Findings

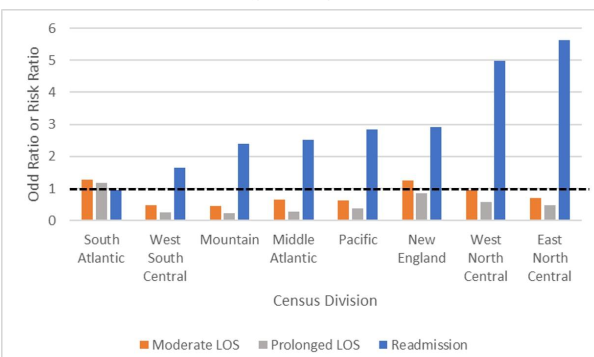
In this retrospective cohort study, interrelated risk factors of 30-day readmission and LOS for CABG and VR patients were investigated. Factors relevant to healthcare delivery and practice, demography, and comorbidity were analyzed in terms of their p-value significance and compared. The association of readmission and LOS with PAC usage was also investigated.

(i) **Healthcare delivery and practice**:

Hospital location was identified as highly significant factor for LOS and moderately significant for 30-day readmission for CABG and VR patients. However, hospital size was identified as significant for only LOS. The results also demonstrated that higher readmission risk is associated with low LOS patients across most census divisions and hospital sizes in the U.S., as shown in Fig. 3.3(a) and Fig. 3.3(b), respectively. Besides, significant differences in LOS and 30-day readmission patterns were observed. For example, Odds Ratio (OR) for readmission varied from 0.95 in South Atlantic to 5.63 in East North Central; Relative Risk (RR) for prolonged LOS varied from 0.24 in Mountain division to 1.17 in South Atlantic division (Fig. 3.3(a)). Identical variations were detected across different hospital sizes as well (Fig. 3.3(b)); the readmission OR varied from 0.28 for small hospitals (with bed size < 5) to 2.34 for hospitals with a bed size range of 100-199. RR for prolonged LOS varied from 0.47 for hospitals with bed size 300-499 to 6.69 for hospitals with a bed size of 06-99. These outcomes indicate differences in medical practices and non-uniform care for patients across the U.S. census divisions and hospitals.

Hospital resources, e.g., having teaching facility in the hospital also influenced LOS and readmission. Having such facilities, in general, lead to additional diagnosis and use of intensive care units for the patients [89], and resulted in significantly higher moderate and prolonged LOS, and lower readmission risk.

(a) Distribution of OR/RR across the census divisions for LOS and readmission; the dotted line at OR/RR = 1 indicates the referent census division in this case is: East South Central.



(b) Distribution of OR/RR across the bed size range for LOS and readmission; the dotted line at OR/RR = 1 indicates the referent bed size range in this case is: 500+.

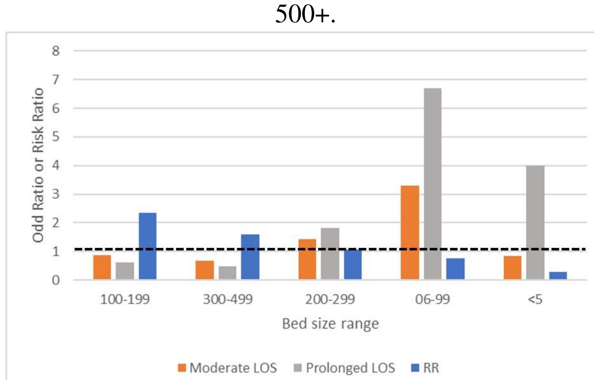


Figure 3.3: Distribution of Odd Ratio (Readmission) and Risk Ratio (LOS)

(ii) **Demographics**: The analysis showed that social attributes, demographic conditions, and support infrastructure influence 30-day readmission more than LOS. Gender, race, and age affected both readmission and LOS, which is consistent with previous findings [11, 33, 34, 35]. Female patients are more likely to be at risk for readmission and longer inpatient hospital stay. African American patients also have higher associations with both readmission and LOS compared to Caucasians [11, 33, 34, 35, 36, 90]. However, marital status affects readmission rates, but not inpatient hospital stays. Divorced patients showed an increased likelihood of readmission but no significant increased likelihood on LOS. Overall, it can be inferred that those patients who had less care or support structure after discharge from an acute-care hospital, such as divorced and female patients, had a higher risk for readmission.

(iii) **Patient comorbidity**: Among the specific comorbid conditions that were evaluated in this work (as stated in Table 3.1), Atrial Fibrillation and Acute Myocardial Infarctions had highly significant association with both LOS and readmission. Other comorbidities influenced LOS more than readmission (Fig. 3.2). Atrial Fibrillation and Acute Myocardial Infarction are related to CABG and heart failure and thus, require delicate care, which attributes in the longer LOS and higher risk of readmission. Previous studies also reported that patient comorbidity has significant association with readmission and LOS [2, 35].The overall comorbidity (based on Charlson index) was highly significant for both LOS and readmission risk.

(iv) **PAC referral**: Higher LOS at acute care hospital leads to higher PAC referral and this relationship is consistent across all PAC types (Fig. 3.4). It indicates that patients who are critical and received long period of acute treatment are more likely to be referred to PAC facilities for follow-up treatment. Technically, discharge to HHC is similar to discharge to home with some regular follow up care and hence the RR for higher LOS came out close to the referent value of Home. Readmission risk is not highly significantly associated with PAC referral-most of the PAC types (SNF, IRF and HHC) showed the OR for readmission as almost close to the readmission risk if discharged to home (Fig. 3.4). Only patients referred to LTC demonstrated an overall lower risk for readmission, while those referred to IRF showed a slightly higher possibility of readmission. The patient mix handled by these PAC types might be influencing these associations; patients referred to LTC usually go through prolonged follow-up care which may result in decreasing the chance of readmission.

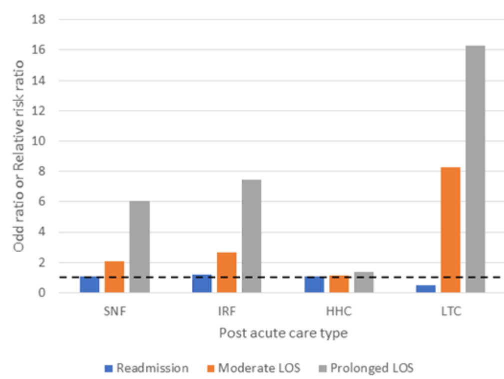


Figure 3.4: Distribution of Odd Ratio (Readmission) or Risk Ratio (LOS) across variation of PAC type

To my knowledge, this study is the first one to compare the risk factors associated with both readmission and LOS for the same sample cohort and analyze the differences and commonality between the factors affecting these important patient metrics. The insights gained in this study will enable the clinicians and providers to identify the factors to jointly manage these interrelated patient metrics. Additionally, for the first time, this study investigates the interaction of the PAC referral with both readmission and LOS for CABG and VR patients, highlighting the effects of different PAC referrals on patient outcomes.

3.5 Summary

The findings from this work identified that non-uniformity in healthcare practice and outcomes exist across geographic locations and that patient demographics, social support infrastructure have strong influence on the readmission for CABG and VR patients. Therefore, to reduce the readmission rate, the healthcare policymakers should work on reducing the effects of racial disparity and on developing support services for the patients who have less social support after discharge from acute hospital. Special patient referral policy and care coordination plans need to be designed for patients with less social support such as females and divorcees. An integrated provider and post-acute care network can help achieve personalized and targeted care coordination plan. It has been also observed that the impact of comorbidity conditions is higher for LOS than for readmission; and PAC referral showed significant association with LOS but not for readmission, except for LTC. The extended follow-up care in LTC could have resulted a decreasing risk of readmission. Therefore, planned interventions such as increasing the inpatient hospital stay for CABG and VR patients with multiple comorbidities and referral to LTC can help in reduced readmission rates for this high-risk cohort.

4. BUILDING PREFERRED POST-ACUTE PROVIDER NETWORK UNDER UNCERTAINTY USING BINARY FIRST STAGE STOCHASTIC PROGRAMMING

4.1 Introduction

Around 40% of Medicare beneficiaries receive PAC after acute hospital discharge, which costs Medicare more than $60 billion in 2015 alone [91]. To ensure a cost effective and well-coordinated smooth transition of patients from hospital to PAC providers, it is essential to develop a PAC PPN. It is also important for the success of value-based purchasing programs. Besides, according to the Institute of Medicine (IOM), increased integration and care-coordination with post acute providers can improve the quality of care as well [92]. However, due to the continuous use of fee for-service policies, healthcare providers are more focused on maximizing the volume and intensity of services rather than enhancing the care-coordination or reducing the costs of post-discharge care. Furthermore, most hospital-based health systems maximize the referral base of hospital admissions through acquisition of outpatient physician practices [93] which results in better return on investment in the current fee-for-service reimbursement environment. As a result, the relationships between acute and post-acute providers across the continuum of care, have remained under developed [92].

As per Affordable Care Act (ACA) policy, the hospital providers are being forced to follow up an entire episode (30,60 or even 90 days post discharge) of the care a patient receives with readmission penalties, bundled payment models and some other total cost of care measures [17]. Therefore, integration with post-acute care (PAC) providers is a strategic imperative that is long due for current health systems. The post-acute industry consists of a variety of services provided in inpatient, outpatient, and home care settings. To date, PAC services are heterogeneous and still poorly coordinated with acute healthcare systems. Moreover, the PAC referral patterns vary widely, raising concerns about substandard care and inflated costs [3, 4]. A long term strategic partnership between the hospitals and PAC providers which is commonly referred as preferred post acute provider networks (PPN), can potentially contribute in mitigating these issues,. The objective of PPN is to facilitate the smooth transitions of patients from hospitals to PAC facilities and to ensure effective care coordination. Through these networks, hospitals and PAC providers can exchange essential clinical information, care management protocols, and, increasingly, share savings. However, the formation of PPN is complex and requires a clear understanding of the referral patterns to PAC providers, financial ability and quality performance of PAC facility, and PAC providers capacity and ability to serve patients from certain geographic and varying levels of acuity.

While forming this network, hospitals need to carefully manage their downstream post acute bed capacity to help avoid upstream congestion delays in emergency and surgical departments. Delayed hospital discharges are one of the major causes of upstream congestion, and these delays often result from the bed capacity shortages in the various post-acute care settings [18]. Unfortunately, PAC is, perhaps, the least understood portion of the healthcare continuum, and comparatively little studies were carried out on the rational planning and effective use of post-acute services. In a robust PAC PPN network, the hospital and the PAC providers should develop a standardized set of protocols and policies that optimize the patient care. To conform to the agreement, hospitals and PAC providers both need to adjust their operational policies and plan for better resource and capacity utilization. Typically, hospitals need to carefully negotiate the right amount of capacity for each type of PAC services in the PPN; too much capacity will lead to inappropriate usage due to supply side effects, while too little will result in delayed hospital discharge and bed-blocking [18, 19]. These decisions are challenging due to the complex nature of patient flow from the acute hospital to post-acute settings that comprises of uncertainties of patient arrival, patients length of stay, availability of service providers and other resources in the system. These uncertainties call for stochastic optimization to generate the best decisions which are supposed to guide the operational planning to form a PAC PPN.

In this work, a novel framework is proposed to facilitate the formation of a PAC PPN and then simulate its implementation through an operational planning and resource adjustment model. The two-stage stochastic model incorporates multiple Skilled Nursing Facilities (SNF) which are in preferred partnership with multiple ACFs. The model specifies the patient referral schedule from ACF to SNF included in the network and the numbers of patients admitted in the SNF. Also, the optional requirement of outsourcing additional beds and nurses for SNF as well as the number of extra nursing hours in SNF can be estimated from the model.

4.2 Problem description

Post-acute care (PAC) provides treatment for patients following hospital discharge to further improve patient outcomes, readmission rates, mortality, and functional disability. To ensure availability of PAC service, when needed, and for its maximum utilization, an effective care coordination from acute care facilities (ACF) to PAC facilities is a long due necessity, i.e., both ACF and PAC facilities require an agreement to develop a Post Preferred Network (PPN) so that both parties can benefit while patients obtain appropriate health care. As a requirement of this agreement, PAC facilities need to adjust their resource capacity and operational planning. So, the target is to propose and formulate an operational planning model for multiple SNFs which are in contract with multiple ACFs under uncertainty using stochastic programming. In our problem statement, the availability of a permanent nurse of SNF and the number of discharged patient from SNF in a given day are considered as a stochastic variable.*The class of the problem becomes a two-stage stochastic mixed integer model that involves binary variable in first stage and both continuous and integer variable in the second stage*.

The proposed plan is to develop an operational planning model for multiple SNFs which are included in a post preferred network of multiple ACFs. Our model involves the decision of scheduling patient referral from ACF to SNF included in the network, the additional beds and nurses to outsource for SNF, number of overtimes of nursing hours in SNF, numbers of patients unable to admit in the SNF. Here, bed outsourcing means sending patients to some other skilled nursing facilities under mutual collaboration and nurse outsourcing means hiring some additional nurses temporarily. According to a presumed contract agreement, SNF needs to fulfill a pre-fixed percentage of demand from ACF. Beyond this minimum level, SNF should try to fulfill the rest of the demand as much as possible otherwise a waiting cost (like a penalty cost) will be incurred for keeping the patients in ACF for more days. This penalty cost is introduced because ACF will not be able to admit some new emergency patient due to bed blocking. To ensure proper care, ACF wants the SNF to have sufficient nursing staff (4 per patient day (PPD) minimum) to provide nursing and related services.

In the first stage, the number of patients from ACF ready to be discharged to SNF, the number of SNF beds contracted for an ACF and the patient preference weightage for SNFs included in the network are known. In the proposed two stage formulation, the first stage decisions are made 'here and now' before observing future uncertainty. There are two first stage decision variables. Those are the decisions of scheduling each ACF patient referral to a SNF considering patient preference and SNF capacity . These decisions are planned ahead of a finite planning horizon m days. The first stage objective is minimizing the patient preference weightage distribution to the referred SNF and the penalty of not being able to schedule a patient to any SNF in the network.

The second stage decisions represent the recourse decisions to be made after uncertainty is realized. In the second stage, it is observed that the realization of the stochastic parameters which include the availability of permanent nurses and number of patients discharged from SNF. The second stage decision variables are number of additional beds required to outsource, temporary nurses required to hire, number of referred patients that can't be admitted, overtime hours for nurses, and number of occupied beds when the first stage decisions are fixed. The number of beds occupied on day i at SNF j is considered as an auxiliary variable in the second stage as it is scenario dependent and also dependent upon the number of admitted patients which is related to another second stage variable (number of referred patients that can't be admitted). The second stage objective is minimizing the outsourcing cost for additional beds, cost of hiring temporary nurses, waiting cost of the patients who were not admitted due to resource shortage and overtime nursing cost of regular nurses.

In this problem, there are two stochastic parameters. Availability of permanent nurses of SNF on a particular day is a random variable. The number of ACF *k* patients discharged from SNF *j* on day *i* under scenario ω, is also a random variable. Here ω is the set of scenarios ($\omega \in \Omega$) where the scenarios are formulated considering these two uncertain parameters. The operational planning model is intended to design for a particular planning horizon (time period *m* days). *m* can be set based on average length of stay of patients in the SNF.

4.3 Problem formulation and mathematical modeling

Data

I : Set of days in planning horizon, where $I = \{1, 2, 3, ..., m\}$, indexed by i

J : Set of SNFs, where $J = \{1, 2, 3, ..., n\}$, indexed by j

K : Set of ACFs, where $K = \{1, 2, 3, q\}$, indexed by k

P_{ik} : Set of patients on day i at ACF k ready to be discharged to SNF, where $P_{ik} = \{1, 2, 3, ..., d_{ik}\}$, indexed by p

Ω : Set of all scenarios, indexed by ω where the scenario is the realization of uncertain parameters $\{n^{\omega}_{ij}, dc^{\omega}_{ij}\}$

dc^{ω}_{ij} : Number of patients discharged on day i from SNF j under scenario ω, assuming $dc^{\omega}_{0j} = 0$

p_{ω} : Probability of scenario $\omega \in \Omega$

d_{ik} : Number of patients from ACF k ready to be discharged to SNF on day i

c_{jk} : Number of SNF beds contracted for ACF k from SNF j

w_{ijkp} : Patient preference weightage provided by patient p at ACF k for SNF j on day i

s^p : Penalty for sending patient to dummy SNF s

n_{ij}^{ω} : Number of permanent nurses on day i at SNF j under scenario ω

c_j^b : Cost to SNF j for outsourcing one bed from other SNF facilities

c_j^n : Cost to SNF j for hiring one nurse from other SNF facilities

M_j : Budgetary limit of SNF j for additional beds and nurses

H : Shift length in hours

ρ_{jk} : Minimum percentage of demand to be satisfied by SNF j from ACF k

c_k^{los} : Daily waiting cost per patient boarded in ACF i (waiting for SNF admission)

c_j^o : Hourly overtime cost of regular nurses in SNF j

B_j : Number of permanent beds in SNF j

τ : Minimum required SNF nursing hours per patient per day

γ : factor that weighs the first stage objective value to the second stage objective value

Decision Variables

First Stage Variables:

$$x_{ijkp} = \begin{cases} 1, & \text{if the patient } p \text{ from ACF } k \text{ is scheduled to refer to SNF } j \text{ on day } i \\ 0, & \text{otherwise} \end{cases}$$

$$x_{ikp}^s = \begin{cases} 1, & \text{if the patient } p \text{ from ACF } k \text{ is scheduled to refer to SNF } s \text{ on day } i \\ 0, & \text{otherwise} \end{cases}$$

Second Stage variables:

$y_{ijk}^{p^\omega}$: Number of patients from ACF k not admitted on day i by SNF j under scenario ω, assuming $y_{0jk}^{p^\omega} = 0$ for ω in Ω

$y_{ij}^{b^\omega}$: Number of beds outsourced on day i at SNF j under scenario ω

$y_{ij}^{n^\omega}$: Number of temporary nurses hired on day i at SNF j under scenario ω

$y_{ij}^{h^\omega}$: Number of overtime hours of permanent nurses on day i at SNF j under scenario ω

$y_{ij}^{o^\omega}$: Number of beds occupied at the beginning of day i at SNF j under scenario $\omega,$ assuming $y_{0j}^{o^\omega} = 0$ for ω in Ω

Two stage formulation:

Stage 1:

$$\min \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{p\in P_{ik}} pw_{ijkp}x_{ijkp} + \sum_{i\in I}\sum_{k\in K}\sum_{p\in P_{ik}} s^p x_{ikp}^s + E[Q(x,\widetilde{\omega})] \tag{4.1a}$$

subject to

$$\sum_{j\in J} x_{ijkp} + x_{ikp}^s = 1, \forall i \in I, k \in K, p \in P_{ik} \tag{4.1b}$$

$$-\sum_{p\in P_{ik}} x_{ijkp} \geq -c_{jk}, \forall i \in I, j \in J, k \in K \tag{4.1c}$$

$$x_{ijkp}, x_{ikp}^s \; binary, \tag{4.1d}$$

where, for each outcome (scenario) $\omega \in \Omega$ of $\widetilde{\omega}$,

Stage 2:

$$Q(x,\omega) = \min \gamma * \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}(c_k^{los} y_{ijk}^{p^\omega} + c_j^b y_{ij}^{b^\omega} + c_j^n y_{ij}^{n^\omega} + c_j^o y_{ij}^{h^\omega}) \tag{4.2a}$$

subject to

$$-c_j^b y_{ij}^{b^\omega} - c_j^n y_{ij}^{n^\omega} \geq -M_j, \forall j \in J, \forall i \in I \tag{4.2b}$$

$$\sum_{p\in P_{ik}} x_{ijkp} - y_{ijk}^{p^\omega} - \rho_{jk} \sum_{p\in P_{ik}} x_{ijkp} \geq 0, \forall i \in I, \forall j \in J, \forall k \in K \tag{4.2c}$$

$$-\sum_{k\in K}(\sum_{p\in P_{ik}} x_{ijkp} - y_{ijk}^{p^\omega}) - y_{ij}^{o^\omega} + y_{ij}^{b^\omega} \geq -B_j, \forall i \in I, \forall j \in J \tag{4.2d}$$

$$-\sum_{k\in K}(\sum_{p\in P_{(i-1)k}} x_{(i-1)jkp} - y_{(i-1)jk}^{p^\omega}) + y_{ij}^{o^\omega} - y_{(i-1)j}^{o^\omega} \geq -dc_{(i-1)j}^{\omega}, \forall i \in I \setminus \{1\}, \forall j \in J \tag{4.2e}$$

$$H y_{ij}^{n^\omega} + y_{ij}^{h^\omega} - \tau y_{ij}^{o^\omega} \geq -H n_{ij}^{\omega}, \forall j \in J, \forall i \in I \tag{4.2f}$$

$$y_{ijk}^{p^\omega}, y_{ij}^{b^\omega}, y_{ij}^{o^\omega}, y_{ij}^{n^\omega} \; integer \tag{4.2g}$$

$$y_{ij}^{h^\omega} \geq 0 \tag{4.2h}$$

The objective function (4.1a) minimizes the patient preference weightage distribution to the referred SNF and expected recourse objective function. The first term indicates the summation of patient preference weightage distribution corresponding to patient referral decision, second term indicates the penalty to refer a patient to dummy SNF (not being able to schedule the referral of a patient) and the third term indicates the expected value of the recourse objective function.

Constraint (4.1b) forces the requirement that each patient from ACF will be scheduled to refer to only one SNF. Constraint (4.1c) is necessary to ensure that the total number of referred patient to a particular SNF does not exceed the available bed capacity of the SNF. Constraint (4.1d) indicates the binary restrictions of the first stage decision variables.

The objective function (4.2a) minimizes the outsourcing cost for additional beds, cost of hiring temporary nurses, cost of overtime hours for regular nurses and the penalty cost for declining a patient from admission to SNF due to unavailability of resources.

Constraint (4.2b) is the budgetary constraint on total outsourcing cost. This constraint ensures that the total cost of additional beds and temporary nurses does not exceed the available budget. Constraint (4.2c) imposes the minimum percentage of demand to be satisfied by SNF j from ACF k. This ensures that each SNF will admit minimum percentage of patients referred from ACF k and hence the number of patients that can't be admitted will be less than or equal to the remaining numbers of the patients after satisfying the minimum percentage of demands. Constraint (4.2d) indicates that for a particular SNF j, the summation of total available empty beds (available permanent beds + number of outsourced beds − occupied beds) and the number of patients who were not admitted to SNF j due to resource shortage will be greater than or equal to the total demand of patients referred from a particular ACF k. Constraint (4.2e) maintains the flow of occupied and discharged beds. This constraint ensures that the summation of total number of patients admitted to SNF j on a particular day i and the number of patients not admitted due to resource shortage equals the total number of patients referred to the SNF j from a particular ACF k. Constraint (4.2f) considers that the total number of nursing hours should be greater than or equal to the required per patient day (PPD) hours for the total occupied beds on a particular day i. The total number of nursing hours consists of shift length multiplied by total number of permanent regular nurses and temporary nurses outsourced on a particular day i and the total number of overtime nurses. Constraint (4.2g) indicates the integrality restrictions and (4.2h) indicates the non-negativity restrictions.

4.4 Solution

4.4.1 Binary first stage algorithm

Our proposed two stage stochastic problem belongs to the class two-stage stochastic mixed integer model that involves pure binary variable in first stage and arbitrary in the second stage. We used the existing solution approach Binary First Stage (BFS) algorithm derived by Laporte and Louvex [60] to solve our model. In the following subsections the details of computational study involving description of test instances generation and results are reported.

4.4.2 Computational study

To gain insights about the outcome of the proposed model, a computational study has been performed implementing the Binary First Stage (BFS) algorithm. The BFS algorithm was implemented in C++ using the IBM CPLEX Callable Library CPLEX12 in the Microsoft Visual Studio 2015 environment. Computational experiments were run on a DELL X55355 Windows® workstation with an Intel®323Xeon® X processor, 2.66GHz and 12GB RAM. A set of hypothetical test instances were generated using some parameter and random variable distribution value extracted from a New York based retrospective publicly available data set [94, 95] and some are extracted from existing literature and articles [96, 97, 98]. The BFS algorithm was run up to 3600 sec with a termination gap ϵ set at $e - 6$. The results were compared with the DEP solution.

4.4.2.1 Test instances generation

Test instance data were randomly generated using the uniform distribution with different parameter values and poisson distribution for patient discharge data. The input parameter values are specified in Table 4.1. In total, 9 test instances in 3 sets were generated where the sets were created specifying small, medium, and large network. The network size was set based on the days in planning horizon and also on the numbers of participating ACF and SNF in the PAC PPN model.

The scenario numbers were also set in an increasing order like 5,10,15 for small, medium, and large set respectively. The generated test instances are given in Table 4.2. Each scenario is assumed to have equal probabilities.

Table 4.1: The input parameter values for the test instances

Parameter	**Distribution**
Number of patients discharged from ACF	Poisson (λ = 10.5)
Number of permanent beds in SNF	Uniform (10, 15)
Outsourcing bed cost/day	Uniform (200, 300)
Temporary nurse cost/day	Uniform (200, 250)
Waiting cost of patient in ACF/day	Uniform (1500, 2000)
Overtime cost for nurses/hour	Uniform (50, 55)
Random Variable	**Distribution**
Number of available nurses in SNF	Uniform (8, 10)
Number of discharged patients from SNF on a day	Poisson (λ = 6.75)

Table 4.2: Set sizes for each instance

Size	Instance	# of days	# of SNFs	# of ACFs	# of scenarios
Small	S1	3	5	3	5
	S2	4	4	4	5
	S3	3	6	5	5
Medium	M1	5	10	5	10
	M2	6	8	7	10
	M3	5	12	6	10
Large	L1	7	18	9	15
	L2	8	20	10	15
	L3	7	16	10	15

4.4.2.2 Results

Detailed computational results for the test sets of small network (S1, S2, S3), medium network (M1, M2,M3) and large network (L1,L2,L3) are reported in Table 4.3. In Table 4.3, BFS represents

Table 4.3: Solution DEP vs Binary First Stage

	DEP			BFS				
Instance	Best Solution	Gap	CPU Time	LB	UB	# of iterations	Gap	CPU Time
S1	3816.93	0.00%	0.11	3790.45	3935.26	18	3.68%	3600
S2	5824.5811	0.01%	1.34	5720.24	5878.64	16	2.69%	3600
S3	2524.2937	0.02%	0.3	2467.2	2557.27	13	3.52%	3600
M1	4072.1195	0.01%	2.133	4064.14	4078.24	36	0.34%	3600
M2	1.27E+11	2.41%	3600	1.27E+11	1.30E+11	24	2.30%	3600
M3	4799.4517	0.01%	115.389	4793.95	4794.45	202	0.01%	3600
L1	10653.03	0.07%	3600	9525.66	10778.6	33	11.61%	3600
L2	-	-	-	12896.5	14378.3	98	10.31%	3600
L3	-	-	-	11669.2	12447.3	95	6.25%	3600

results using Binary First Stage algorithm and DEP represents the results solving the Deterministic Equivalent Problem (DEP) of the instance. CPU time represents the total computational time by CPU in seconds to attain the best solution for the instances. For DEP, % Gap indicates the CPLEX MIP gap % reported for the instances after reaching to DEP optimal solution or one hour (3600 sec) run time. However, optimality or any good solution was not attained for DEP of L2 and L3 instances after stipulated time of one hour and therefore not reported in Table 4.3. For BFS results, %Gap is the percentage gap between the lower bound (LB) and the upper bound (UB) value after stipulated run time 3600 sec.

From Table 4.3 it can be observed that, for small PPN with small number of scenarios DEP attained optimal solutions in less time than BFS. However, for the large PPN with increased number of scenarios (L2 and L3) CPLEX MIP solver applied to DEP could not achieve any good solution (gap found 100%) after stipulated run time 3600 sec. So clearly the results indicate the advantage and requirement of BFS algorithm over DEP for larger network and instances. The BFS algorithm stopped after the stipulated run time 3600 sec. We would definitely expect improvement in closing the optimality gaps if the algorithm run time is increased. We could not compare the performance or results from our model with current practice or any existing model because our model is the first mathematical framework proposed to develop PAC PPN. Still for a very basic comparison, we ran the same model considering without PPN setting the contracted SNF capacity to regular permanent number of beds in SNF, minimum percentage of demand to be satisfied by SNF as 0 and forcing the second stage variables indicating the options of outsourcing beds and hiring temporary nurses as 0. As per our intuition, in every instance without PPN model provided the objective value higher than the model with PPN. This is expected because the ACF cannot send some patients to SNF due to lack of bed capacity and hence it increased the patient waiting cost in ACF and also the penalty cost of referring a patient to dummy SNF. In summary, implementing a PAC PPN can reduce patient hospital stay costs, and if implemented, both participating entities ACFs and SNFs can benefit from being able to admit more patients.

4.5 Summary

This work introduced a stochastic optimization model and solution for developing a PAC PPN network involving multiple ACFs and SNFs. The framework for PAC PPN was modeled as a two-stage stochastic model where the first stage variables are binary, and the second stage has both integer and continuous variables. BFS algorithm was used to solve this class of problem. Our computational results using randomly generated test instances suggest that our decomposition based BFS algorithm performs better with increases in the number of scenarios than CPLEX MIP solver which was used to solve the DEP formulation. Our results also indicates that possible partnership between hospitals and PAC providers in the form of a PAC PPN could facilitate smooth transitions between care settings increasing access to PAC which would be beneficial for reducing patient cost and aggregated system optimization involving both hospitals and PAC providers.This PPN can facilitate immediate and consistent access to high-quality PAC services, increase hospital throughput, reduce the average length of stay, and a more efficient discharge process.

5. SUMMARY AND CONCLUSIONS

In this section, the overall contributions of this dissertation are summarized. Potential future extensions beyond the scope of this dissertation are also outlined.

5.1 Summary of potential research contributions

To improve the care coordination and quality for acute care patients, hospitals are forming PAC PPN. While (1) few hospitals are looking to buy or integrate PAC services as a part of their services, (2) others are looking to align with existing PAC providers through a standardized PPN. This dissertation can contribute to strategic decision making for both cases, especially, the second one. Understanding the referral patterns is critical to streamline the PAC capacities and standardize the referral practices. So, primarily, the prevailing PAC referral pattern for CABG or VR patients in the U.S. was characterized; it can provide an estimated PAC needs for the PAC PPN modeling. Later, analyzing 49 acute hospitals data from all census divisions of the U.S., the impact of the variation of PAC types on readmission and LOS was explored. However, important modeling features, e.g., true enrollment of patients in PAC and discharge medication, were unavailable in the data set. Further extension of the work including those features would help in gaining more insights to make a robust PPN agreement. Besides, the first two works of my research will serve as a benchmark for identifying risk factors for patients with CABG and VR procedures and assist in improving actions to reduce avoidable readmission scenarios.

The third work of this dissertation, the framework to implement a SNF PPN for CVD patients will work as a decision-making tool for the PPN operational planning under uncertainty. The modeling approach can be extended to develop PPN involving other PAC types, which will lead to the development of an aggregate care coordination model for the acute care hospitals. Overall, it will help pioneering a cost-effective and patient metric driven healthcare system.

5.2 Further research directions

Increased usage of PAC services and geographic variation in PAC costs led healthcare researchers to focus on PAC related research which is unfortunately one of the least understood portions of healthcare continuum. An appropriate care coordination between the entities of healthcare care continuum is very important to improve the healthcare affordability and quality. This dissertation will undoubtedly work as a benchmarking guideline for further improvement of developing a preferred post-acute network. There are many ways to further improve and continue this research in this direction. First of all, we had limited information on patient socioeconomic status, hospital billing, important variables related to patient condition during discharge such as discharge medication. If this information can be accessed or collected, the predictive model and referral pattern can definitely be improved and validated as well. Second, limited information was available regarding the PAC facilities, information on the PAC location, quality, and type of service, patient adherence, and length of stay at the PAC would have facilitated analysis of the patient metrics and outcome. Finally, since data on number of beds and health professionals working in the PACs were not available, the number of PAC facilities was used as a proxy variable for PAC capacity. Configuring these unavailable information and data, a better performing predictive patient referral model-based research can be carried out in the future.

A future extension to this study can also consider true enrollment of patients into the PAC and analyze discrepancies between referral and enrollment patterns. Further studies should also include larger data sets, especially including more hospitals from each census region, and multilevel mixed modeling should be performed for the analysis to reduce the clustering effects of patients within facilities within geographic regions. In future, inclusion of supportive information from the PAC facilities could allow to account for the PAC effectiveness and result in more robust and insightful findings.

The PAC PPN model proposed in this dissertation is the very first mathematical work to shape the formation of an agreement between ACF and PAC within an integrated network. This model lacks some important information like patient insurance coverage, hospital billing which would undoubtedly help in gaining more insights to make a robust PPN agreement. Improvements to my current proposed framework unveils a vast field of potential research. From the complication of solution perspective of mixed integer stochastic problem, integer L shaped decomposition can be implemented where first stage not only includes binary variables but also a combination of binary with mixed integer variables which is a more realistic case. The stochastic model represented in this dissertation is a risk neutral formulation, but in reality, the scenario and situation in healthcare are mostly not risk neutral. An obvious improvement of this proposition would be to extend the risk-neutral formulation to include a risk measure and to include a cost sharing aspect in our model given that relevant data is available.

Finally, the models and analysis presented in this dissertation is a particular data set and patient cohort based. But the approach used in the works can be extended or applied to another domain of patient cohort and larger data set. For the PAC PPN model, patient cohort specific constraints can be generated and incorporated into the model to make the agreement decision and network more insightful.

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APPENDIX

Table A1: Summary statistic of the variables included in the multinomial logistic regression model across the discharge destinations (All values listed as x(y) denote x =number of count, y= % for a particular discharge location; values listed as x+y denote x= mean and y= standard deviation; values listed as x[y,z] denote x= median, y= 1st quartile and z=3rd quartile; p-values are generated from bivariate chi-square test)

Variables	Discharged to						p-value
	Home	HHC	SNF	IRF	LTCH	Others	
Regional (Hospital location)							
Census Division:							
East North Central	704(4.95)	548(3.85)	252(1.77)	215(1.51)	17(0.12)	21(0.15)	
East South Central	2007(14.11)	390(2.74)	166(1.17)	274(1.93)	47(0.33)	19(0.13)	
Middle Atlantic	329(2.31)	2125(14.94)	497(3.49)	139(0.98)	15(0.11)	8(0.06)	
Mountain	283(1.99)	9(0.06)	63(0.44)	7(0.05)	1(0.01)	1(0.01)	
New England	324(2.28)	606(4.26)	280(1.97)	156(1.10)	15(0.11)	10(0.07)	<0.001
Pacific	118(0.83)	67(0.47)	52(0.37)	0(0.00)	3(0.02)	5(0.04)	
South Atlantic	1039(7.3)	382(2.69)	165(1.16)	180(1.27)	24(0.17)	30(0.21)	
West North Central	324(2.28)	226(1.59)	148(1.04)	12(0.08)	7(0.05)	7(0.05)	
West South Central	699(4.91)	873(6.14)	98(0.69)	185(1.30)	35(0.25)	17(0.12)	
Hospital/Provider							
Bed Size Range:							
<5	2(0.01)	1(0.01)	2(0.01)	0(0.00)	0(0.00)	1(0.01)	
06-99	26(0.18)	24(0.17)	9(0.06)	6(0.04)	0(0.00)	1(0.01)	
100-199	758(5.33)	309(2.17)	243(1.71)	124(0.87)	8(0.06)	12(0.08)	<0.001
200-299	1204(8.46)	502(3.53)	232(1.63)	125(0.88)	39(0.27)	26(0.18)	
300-499	1221(8.58)	976(6.86)	362(2.54)	372(2.62)	28(0.20)	32(0.22)	
500+	2616(18.39)	3414(24)	873(6.14)	541(3.80)	89(0.63)	46(0.32)	
Hospital Status:							
Urban	5630(39.58)	4602(32.35)	1501(10.55)	1064(7.48)	161(1.13)	110(0.77)	<0.001
Rural	197(1.38)	624(4.39)	220(1.55)	104(0.73)	3(0.02)	8(0.06)	
Teaching Facility Affiliation	4863(39.5)	4069 (33.03)	1124(9.1)	441(3.6)	108 (0.9)	124 (1.0)	<0.001
Patient demographic							
Gender:							
Male	4473(31.25)	3874(27.24)	980(6.89)	728(5.12)	95(0.67)	84(0.59)	<0.001
Female	1354(9.52)	1352(9.51)	741(5.21)	440(3.09)	69(0.49)	34(0.24)	
Marital Status:							
Married	3832(26.94)	3527(24.80)	768(5.40)	579(4.07)	74(0.52)	51(0.36)	
Divorced	682(4.79)	483(3.40)	227(1.60)	156(1.10)	27(0.19)	16(0.11)	<0.001
Single	881(6.19)	691(4.86)	293(2.06)	168(1.18)	25(0.18)	36(0.25)	
Widowed	432(3.04)	525(3.69)	433(3.04)	265(1.86)	38(0.27)	15(0.11)	
Race:							
Caucasian	4705(33.08)	4524(31.81)	1532(10.77)	977(6.87)	118(0.83)	90(0.63)	
African American	868(6.10)	455(3.20)	137(0.96)	155(1.09)	37(0.26)	23(0.16)	
Asian	64(0.45)	73(0.51)	9(0.06)	10(0.07)	2(0.01)	0(0.00)	<0.001
Hispanic	38(0.27)	24(0.17)	6(0.04)	8(0.06)	2(0.01)	1(0.01)	
Native American	41(0.29)	27(0.19)	6(0.04)	9(0.06)	2(0.01)	2(0.01)	
Others	111(0.78)	123(0.86)	31(0.22)	9(0.06)	3(0.02)	2(0.01)	
Age in years	59.4+11	63.6+11.2	72.3+10.00	70.3+10.5	67.9+10.5	63+12.2	<0.001
Related factors of PAC referral discharge							

Length of stay, days	7[5,10]	7[5,11]	11[8,16]	12[8,18]	25[20,37]	11[7,17]	<0.001
Charlson index	2[1,3]	1[1,3]	2[1,4]	3[1,4]	3[2,5]	2[1,4]	<0.001
Comorbidity and diagnosis information							
Coronary Bypass of Two Coronary Arteries	1757(14.3)	1416(11.5)	453(3.7)	188(1.5)	47(0.4)	43(0.3)	0.13
Coronary Bypass of Four or More Coronary Arteries	478(3.9)	352(2.9)	85(0.7)	60(0.5)	2(0.02)	9(0.1)	0.004
Coronary Bypass of Three Coronary Arteries	1423(11.6)	915(7.4)	256(2.1)	126(1.0)	23(0.2)	31(0.25)	<0.001
Coronary Bypass of one Coronary Artery	1012(8.2)	916(7.4)	247(2.0)	103(0.8)	27(0.2)	24(0.2)	0.026
Open Aortic Valve Replacement Tissue Graft	161(1.3)	269(2.2)	153(1.2)	45(0.4)	11(0.1)	18(0.15)	<0.001
Open Aortic Valve replacement	188(1.5)	172(1.4)	69(0.6)	44(0.4)	6(0.05)	9(0.1)	<0.001
Diabetes Mellitus without complications	1800 (14.6)	1236 (10.0)	397 (3.2)	176 (1.4)	34 (0.3)	53 (0.4)	0.0002
Tobacco Use disorder	1588(12.9)	848(6.9)	163(1.3)	80(0.6)	22(0.2)	31(0.3)	<0.001
Atrial Fibrillation	1415(11.5)	1305(10.6)	567(4.6)	248(2.0)	57(0.5)	60(0.5)	<0.001
Unspecified Hypertension	3149(25.6)	2601(21.1)	656(5.3)	257(2.1)	42(0.3)	77(0.6)	<0.001
Coronary Atherosclerosis	5418(44.0)	4226(34.3)	1199(9.7)	538(4.4)	104(0.8)	132(1.1)	<0.001
Intermediate Coronary Syndrome	1431(11.6)	867 (7.0)	220 (1.8)	100 (0.8)	11(0.1)	28 (0.2)	<0.001
Hyperlipidemia	3851(31.3)	2734 (22.2)	752(6.1)	349 (2.8)	51(0.4)	87(0.7)	<0.001
Posthemorrhagic Anemia	1918(15.6)	1415 (11.5)	531(4.3)	249(2.0)	60 (0.5)	56(0.5)	<0.001
Acute Myocardial Infarction	1233(10.0)	885(7.2)	351(2.8)	161 (1.3)	40(0.3)	35(0.3)	<0.001
Congestive Heart Failure	938(6.6)	935(6.6)	565(3.9)	389 (2.7)	79(0.6)	34(0.3)	<0.001
Anemia, Unspecified	807(5.7)	707 (4.9)	263(1.8)	211 (1.5)	29(0.2)	20(0.1)	<0.001
Pulmonary Collapse	900(6.3)	1330 (9.3)	368(2.6)	239(1.7)	46 (0.3)	24(0.2)	<0.001
Acute Kidney Failure, Unspecified	520(3.7)	435(3.1)	318(2.2)	256 (1.8)	73(0.5)	24(0.2)	<0.001

Table A2: Risk ratios, p-values and 95% CI of the predictor variables in the model P value notation: ***: p $\leq$ 0.001; **: 0.001 $<$ p $\leq$ 0.01; *: 0.01 $<$ p $\leq$ 0.05; no asterisk: p $>$ 0.05

Variables	Risk Ratio p-value (95% CI)							
	HHC		SNF		IRF		LTCH	
Regional (Hospital location)								
Census Division: East South Central (Reference)								
East North Central	1.5***	(1.3, 1.7)	1	(0.8,1.2)	2.8***	(2.0, 3.7)	1.2	(0.6, 2.1)
Middle Atlantic	5.4***	(4.7, 6.2)	2.9***	(2.3,3.4)	1.8***	(1.4, 2.2)	2.1**	(1.2, 3.7)
Mountain	0.3***	(0.1, 0.4)	1.6**	(1.1,2.1)	6.7***	(4.3,10.4)	0.5	(0.0, 2.5)
New England	1.7***	(1.4, 1.9)	3.5***	(2.8,4.2)	1.5***	(1.1, 1.8)	2.3**	(1.3, 4.1)
Pacific	2.5***	(1.7, 3.7)	1.9***	(1.3,2.7)	0.0***	(0.0, 0.0)	1.9	(0.5, 6.9)
South Atlantic	3.6***	(2.9, 4.5)	2.4***	(1.7,3.3)	0.8	(0.5, 1.0)	1.9	(0.8, 3.9)
West North Central	2.0***	(1.7, 2.4)	4.7***	(3.5,6.1)	0.2***	(0.1, 0.3)	1.6	(0.6, 3.9)
West South Central	9.2***	(7.6,11.1)	3.0***	(2.1,4.3)	3.0***	(2.2, 3.9)	13.2***	(6.7, 25.6)
Hospital/Provider								
Bed Size Range: 500+(Reference)								
<5	0.4**	(0.0,4.5)	3.3**	(0.2,38.1)	0.1***	(0.0,0.1)	0.4***	(0.3, 0.4)
06-99	0.5*	(0.2, 0.8)	2.4**	(0.8,6.24)	1.0**	(0.3, 2.8)	0.0***	(0.0, 0.0)
100-199	0.2***	(0.1, 0.2)	0.9**	(0.6,1.2)	0.9**	(0.6, 1.2)	0.5**	(0.1, 1.2)
200-299	0.7***	(0.5, 0.8)	0.5***	(0.4,0.6)	0.5***	(0.3, 0.6)	1.1**	(0.6, 2.1)
300-499	0.7***	(0.5, 0.8)	0.4***	(0.3, 0.5)	2.5***	(1.9, 3.2)	1.0**	(0.5, 2.1)
Hospital Status: Urban (Reference)								
Rural	1.1	(0.8, 1.4)	1.4*	(1.0,2.0)	0.9	(0.6, 1.4)	0.2	(0.1, 1.1)
Teaching Facility Affiliation	0.4***	(0.3, 0.4)	0.2***	(0.1,0.3)	0.4***	(0.3, 0.6)	0.1***	(0.1 ,0.3)
Patient demographic								
Gender: Male (Reference)								
Female	1.3***	(1.1, 1.4)	2.0***	(1.7, 2.3)	1.6***	(1.3, 1.9)	1.9**	(1.2, 2.9)
Marital Status: Married (Reference)								

Divorced	1	(0.8, 1.2)	3.1***	(2.4,3.9)	2.3***	(1.8, 3.0)	3.2***	(1.8, 5.7)
Single	1	(0.9, 1.2)	3.4***	(2.7,4.2)	2.1***	(1.6, 2.7)	2.2**	(1.2, 4.1)
Widowed	1.1	(0.9, 1.3)	2.0***	(1.6,2.5)	1.9***	(1.5, 2.5)	2.6***	(1.5, 4.6)
Race: Caucasian (Reference)								
African American	1.2*	(1.0, 1.4)	0.9	(0.7,1.2)	1	(0.7, 1.2)	1.61	(0.9, 2.8)
Asian	1.6*	(1.0, 2.6)	0.4	(0.2,1.1)	0.67	(0.2, 1.5)	0.43	(0.0, 4.4)
Hispanic	0.6	(0.3, 1.2)	0.9	(0.3,2.8)	0.71	(0.2, 1.9)	1.24	(0.1,11.5)
Native American	0.5	(0.3, 1.1)	0.5	(0.2,1.4)	1.1	(0.4, 2.9)	0.0***	(0.0, 0.0)
Other	1.1	(0.8, 1.7)	0.8	(0.4,1.4)	0.64	(0.2, 1.4)	0.98	(0.1, 5.2)
Age in years	1.0***	(1.0, 1.0)	1.1***	(1.1,1.1)	1.1***	(1.0, 1.1)	1.1***	(1.0, 1.1)
Related factors of PAC referral discharge								
Length of stay, days	1.0***	(1.0, 1.0)	1.1***	(1.1, 1.1)	1.1***	(1.0, 1.1)	1.2***	(1.1, 1.2)
Charlson index	1.1***	(1.0, 1.1)	1.3***	(1.2,1.3)	1.3***	(1.2, 1.4)	1.3***	(1.1, 1.4)
Comorbidity and diagnosis Information								
Coronary Bypass of Two Coronary Arteries	1.0***	(0.8, 1.1)	1.0***	(0.8,1.3)	0.9***	(0.7,1.2)	1.6***	(0.9,3.0)
Coronary Bypass of Four or More Coronary Arteries	1.2	(0.9, 1.5)	1.2	(0.8,1.6)	1.6**	(1.1, 2.2)	0.6	(0.1, 2.2)
Coronary Bypass of Three Coronary Arteries	0.9	(0.8, 1.1)	0.8	(0.7,1.1)	1.1	(0.8, 1.4)	1.5	(0.7, 2.8)
Coronary Bypass of One Coronary Artery	1	(0.8, 1.1)	0.9	(0.7,1.1)	0.9	(0.7, 1.2)	1.6	(0.8, 3.0)
Open Replacement of Aortic Valve with Tissue Graft	1.5**	(1.1, 1.9)	1.7***	(1.2,2.2)	1.2	(0.8, 1.7)	1.5	(0.7, 3.1)
Open Replacement of Aortic Valve	1	(0.7, 1.3)	1.1	(0.8,1.6)	1.4	(0.9, 2.0)	0.6	(0.2, 1.9)
Diabetes mellitus without complication	0.8**	(0.7, 0.9)	0.9	(0.7,1.0)	0.8	(0.7, 1.0)	0.9	(0.5, 1.4)
Tobacco Use Disorder	0.8**	(0.7, 0.9)	0.7**	(0.6, 0.9)	0.6***	(0.5, 0.8)	0.9	(0.5, 1.6)
Atrial Fibrillation	1	(0.9,1.1)	1	(0.8,1.2)	1	(0.8, 1.2)	1.2	(0.7, 1.8)
Unspecified Hypertension	1	(0.9, 1.1)	1.1	(0.9,1.3)	1.1	(0.9, 1.3)	0.8	(0.5, 1.3)
Coronary Atherosclerosis	0.9	(0.7, 1.1)	0.7*	(0.5,0.9)	0.5***	(0.4, 0.7)	0.5	(0.3, 1.1)
Intermediate Coronary Syndrome	0.9	(0.8,1.0)	0.8	(0.7,1.0)	0.7	(0.5, 0.8)	0.7	(0.3, 1.2)
Hyperlipidemia	0.9	(0.8, 1.0)	0.8*	(0.7,0.9)	0.9	(0.7, 1.0)	0.6*	(0.4, 0.9)
Posthemorrhagic Anemia	0.7***	(0.6, 0.8)	0.8*	(0.7, 1.0)	0.9	(0.8, 1.1)	1.2	(0.8, 1.9)
Acute Myocardial Infarction	1	(0.9, 1.2)	0.8	(0.7,1.0)	0.7**	(0.6, 0.9)	0.7	(0.4, 1.1)
Congestive Heart Failure	1	(0.9,1.2)	1.2	(0.9,1.4)	1.1	(0.9, 1.3)	1	(0.6, 1.6)
Anemia, Unspecified	1.1	(0.9,1.2)	1.1	(0.9,1.4)	1.2	(0.9, 1.5)	0.9	(0.5, 1.6)
Pulmonary Collapse	0.9	(0.8, 1.1)	0.9	(0.7,1.1)	1.2	(0.9, 1.5)	1.2	(0.7, 1.9)
Acute Kidney Failure, Unspecified	0.9	(0.7, 1.1)	1.1	(0.8,1.3)	1.1	(0.8, 1.3)	1.9**	(1.2, 3.0)

Table A3: List of predictor variables included in the multinomial logistic regression model (All values listed as x(y) denote x =number of count, y=% value; values listed as x+y denote x= mean and y= standard deviation; values listed as x[y,z] denote x= median, y= 1st quartile and z=3rd quartile; P-values are generated from bivariate chi-square test)

Variable	Readmitted	Not readmitted	P-value	Short LOS	Moderate LOS	Prolonged LOS	P-value
Census Division:							
East North Central	690 (4.93)	1027 (7.34)	<.001	721 (5.16)	253 (1.81)	743 (5.31)	<.001
East South Central	1802 (12.89)	1096 (7.84)		1011 (7.23)	529 (3.78)	1358 (9.71)	
Middle Atlantic	1501 (10.74)	1496 (10.7)		1406 (10.06)	331 (2.37)	1260 (9.01)	
Mountain	188 (1.34)	176 (1.26)		187 (1.34)	37 (0.26)	140 (1.00)	
New England	554 (3.96)	789 (5.64)		518 (3.70)	168 (1.20)	657 (4.7)	
Pacific	91 (0.65)	150 (1.07)		117 (0.84)	25 (0.18)	99 (0.71)	
South Atlantic	1078 (7.71)	738 (5.28)		695 (4.97)	264 (1.89)	857 (6.13)	
West North Central	288 (2.05)	434 (3.1)		365 (2.61)	70 (0.50)	287 (2.05)	
West South Central	1114 (7.97)	770 (5.51)		1112 (7.95)	149 (1.07)	623 (4.46)	
Bed Size Range:							
<5	3 (0.02)	2 (0.01)	<.001	2 (0.01)	1 (0.01)	2 (0.01)	<.001
06-99	45 (0.32)	22 (0.16)		25 (0.18)	10 (0.07)	32 (0.23)	
100-199	621 (4.44)	798 (5.71)		716 (5.12)	114 (0.82)	589 (4.21)	
200-299	1161 (8.30)	950 (6.79)		846 (6.05)	307 (2.19)	958 (6.85)	
300-499	1338 (9.57)	1639 (11.72)		1350 (9.66)	324 (2.32)	1303 (9.32)	
500+	4138 (29.6)	3265 (23.35)		3193 (22.84)	1070 (7.65)	3140(22.4)	
Marital Status:							
Married	732 (5.24)	835 (5.97)	<.001	601 (4.29)	254 (1.82)	712 (5.09)	<.001
Divorced	4702 (33.63)	3979 (28.46)		4170 (29.82)	910 (6.51)	3601(25.7)	
Single	1060 (7.58)	998 (7.14)		781 (5.59)	329 (2.35)	948 (6.78)	
Widowed	812 (5.81)	864 (6.18)		580 (4.15)	333 (2.38)	763 (5.46)	
Race:							
Caucasian	792 (5.66)	868 (6.21)	<.001	492 (3.52)	341 (2.44)	827 (5.91)	<.001
African American	68 (0.49)	87 (0.62)		63 (0.45)	27 (0.19)	65 (0.46)	
Asian	6221 (44.49)	5507 (39.39)		5389 (38.54)	1395 (9.98)	4944(35.3)	
Hispanic	37 (0.26)	42 (0.30)		37 (0.26)	10 (0.07)	32 (0.22)	
Native American	40 (0.29)	46 (0.33)		38 (0.27)	13 (0.09)	35 (0.25)	
Others	148 (1.06)	126 (0.90)		113 (0.81)	40 (0.29)	121 (0.87)	
Age in years	63.19+11.63	63.73+11.99	0.093	62.06+11.52	64.04+11.83	66.20+12	<.001
Length of stay:							
Short	3517(25.15)	2615(18.70)	<.001	N/A	N/A	N/A	<.001
Moderate	788(5.64)	1038(7.42)		N/A	N/A	N/A	
Prolonged	3001(21.46)	3023(21.62)		N/A	N/A	N/A	
Charlson index	2[1,3]	2[1,3]	<.001	1[0,2]	2[1,3]	4[2,5]	<.001
Gender:							
Male	1905 (13.62)	2012 (14.39)	<.001	1377 (9.85)	684 (4.89)	1856(13.2)	<.001
Female	5401 (38.63)	4664 (33.36)		4755 (34.01)	1142 (8.17)	4168(29.8)	
Hospital Status:							
Urban	544 (3.89)	605 (4.33)	<.001	370 (2.65)	183 (1.31)	596 (4.26)	<.001
Rural	6762 (48.36)	6071 (43.42)		5762 (41.21)	1643 (11.75)	5428 (38.8)	
Teaching Facility Affiliation	6508 (46.54)	5798 (41.47)	<.001	5345 (38.23)	1666 (11.91)	5295 (37.9)	<.001
Discharge Location							
Home	3234 (23.13)	2551 (18.24)	<.001	2944 (21.06)	436 (3.12)	2405 (17.2)	<.001
LTC	96 (0.69)	67 (0.48)		4 (0.03)	130 (0.93)	29 (0.21)	
IRF	496 (3.55)	632 (4.52)		223 (1.59)	334 (2.39)	571 (4.08)	
SNF	715 (5.11)	919 (6.57)		377 (2.7)	459 (3.28)	798 (5.71)	
HHC	2673 (19.12)	2428 (17.37)		2538 (18.15)	415 (2.97)	2148 (15.3)	
Others	92 (0.66)	79 (0.57)		46 (0.33)	52 (0.37)	73 (0.52)	
Coronary Bypass of One Coronary Artery	1655 (11.84)	1363 (9.75)	0.416	1290 (9.23)	386 (2.76)	1342 (9.6)	0.019
Coronary Bypass of Two Coronary Arteries	2304 (16.48)	2065 (14.77)	0.452	1832 (13.10)	607 (4.34)	1930 (13.8)	0.005
Coronary Bypass of Three Coronary Arteries	4152 (29.7)	3602 (25.76)	0.672	3877 (27.73)	703 (5.03)	3174 (22.7)	0.457
Coronary Bypass of Four or More Coronary Arteries	584 (4.18)	501 (3.58)	0.295	482 (3.45)	118 (0.84)	485 (3.47)	0.078
Open Aortic Valve Replacement Tissue Graft	1598 (11.43)	1481 (10.59)	0.097	1367 (9.78)	382 (2.73)	1330 (9.51)	<.001
Open Aortic Valve replacement	1355 (9.69)	1275 (9.12)	<.001	1216 (8.7)	339 (2.42)	1075 (7.69)	<.001
Diabetes Mellitus without complications	2219 (15.87)	1997 (14.28)	0.566	1830 (13.09)	522 (3.73)	1864 (13.3)	0.123
Tobacco Use disorder	406 (2.90)	416 (2.98)	0.001	290 (2.07)	147 (1.05)	385 (2.75)	0.222
Atrial Fibrillation	2108 (15.08)	2244 (16.05)	<.001	1410 (10.08)	864 (6.18)	2078 (14.8)	<.001
Unspecified Hypertension	6508 (46.55)	5798 (41.47)	<.001	5345 (38.23)	1666 (11.92)	5295 (37.9)	<.001
Coronary Atherosclerosis	6966 (49.82)	6244 (44.66)	<.001	5923 (42.36)	1630 (11.66)	5657 (40.4)	<.001
Intermediate Coronary Syndrome	1593 (11.39)	1429 (10.22)	0.581	1252 (8.95)	275 (1.97)	1495 (10.7)	<.001
Hyperlipidemia	4796 (34.30)	4173 (29.84)	<.001	4093 (29.27)	976 (6.98)	3900 (27.9)	<.001
Posthemorrhagic Anemia	2533 (18.12)	2268 (16.22)	0.395	1899 (13.58)	782 (5.59)	2120 (15.2)	<.001
Acute Myocardial Infarction	1618 (11.57)	1526 (10.91)	0.324	632 (4.52)	729 (5.21)	1783 (12.7)	<.001
Congestive Heart Failure	1355 (9.69)	1585 (11.34)	<.001	594 (4.25)	915 (6.54)	1431 (10.2)	<.001

Table A4: Odds ratio for readmission and Risk ratios for LOS with P-values (95% CI) of the Predictor variables in the model P-value notation: no superscript: $P \leq .001$; a: $.001 < P \leq .01$; b: $.01 < P \leq .05$; c: $P > .05$

Variables	Readmission OR (95% CI)		Moderate LOS RR (95% CI)		Prolonged LOS RR (95% CI)	
Census Division: East South Central (Reference)						
New England	2.92^{c}	(0.975,8.751)	1.26^{b}	(1.04,1.53)	0.84^{c}	(0.63,1.12)
Middle Atlantic	2.53^{c}	(0.839,7.638)	0.65	(0.55,0.76)	0.29	(0.23,0.37)
West North Central	4.98^{b}	(1.30,19.04)	0.95^{c}	(0.74,1.21)	0.57^{a}	(0.37,0.87)
East North Central	5.63	(2.15,14.71)	0.71	(0.6,0.84)	0.47	(0.37,0.61)
South Atlantic	0.95^{c}	(0.342,2.626)	1.28^{a}	(1.07,1.53)	1.17^{c}	(0.9,1.52)
West South Central	1.65^{c}	(0.609,4.466)	0.48	(0.42,0.57)	0.26	(0.2,0.34)
Mountain	2.39^{c}	(0.634,9.013)	0.46	(0.35,0.61)	0.24	(0.15,0.38)
Pacific	2.84^{c}	(0.882,9.148)	0.62^{a}	(0.45,0.86)	0.39	(0.22,0.68)
Bed Size range: 500+ (Reference)						
<5	0.28^{c}	(0.021,3.829)	0.83^{c}	(0.11,6.41)	3.98^{c}	(0.3,51.81)
06-99	0.76^{c}	(0.126,4.626)	3.29	(1.86,5.88)	6.69	(2.75,16.34)
100-199	2.34^{c}	(0.946,5.806)	0.87^{c}	(0.74,1.02)	0.61	(0.46,0.82)
200-299	1.07^{c}	(0.486,2.37)	1.42	(1.23,1.64)	1.81	(1.45,2.25)
300-499	1.59^{c}	(0.71,3.534)	0.66	(0.57,0.77)	0.47	(0.37,0.59)
Marital Status: Married (Reference)						
Divorced	1.24	(1.1,1.392)	1.12^{c}	(0.97,1.27)	1.18^{c}	(0.95,1.45)
Single	1.00^{c}	(0.9,1.117)	1.15^{b}	(1.02,1.29)	1.27^{b}	(1.05,1.54)
Widowed	1.09^{c}	(0.967,1.229)	0.97^{c}	(0.85,1.12)	1.16^{c}	(0.95,1.43)
Race: Caucasian (Reference)						
African American	1.73	(1.521,1.96)	1.56	(1.36,1.79)	1.81	(1.48,2.22)
Asian	1.30^{c}	(0.922,1.838)	1.27^{c}	(0.87,1.88)	2.63	(1.52,4.66)
Hispanic	1.20^{c}	(0.665,1.735)	1.34^{c}	(0.72,2.09)	1.74^{c}	(0.65,3.73)
Native American	1.07^{c}	(0.762,1.886)	1.22^{c}	(0.79,2.24)	1.56^{c}	(0.78,3.88)
Other	0.8^{c}	(0.675,1.136)	1.14^{c}	(0.85,1.52)	1.45^{c}	(0.93,2.29)
Age in years	1.00^{b}	(0.992,1)	1.01	(1,1.01)	1.00^{c}	(1,1.01)
Length of stay: Short LOS (Reference)						
Moderate	1.32	(1.21,1.429)	N/A		N/A	
Prolonged	1.63	(1.421,1.864)	N/A		N/A	
Discharge Location: Home (Reference)						
SNF	1.05^{c}	(0.909,1.21)	2.06	(1.75,2.42)	6.06	(4.81,7.59)
IRF	1.21^{b}	(1.041,1.409)	2.64	(2.19,3.17)	7.45	(5.84,9.53)
HHC	1.08^{c}	(0.972,1.195)	1.14^{b}	(1.02,1.26)	1.36	(1.13,1.63)
LTC	0.51	(0.357,0.718)	8.26	(2.77,23.89)	16.29	(55.79,466.7)
Charlson index	1.09	(1.066,1.123)	1.26	(1.22,1.3)	1.61	(1.54,1.68)
Gender: Male (Reference)						
Female	1.14^{a}	(1.05,1.242)	1.33	(1.21,1.46)	1.43	(1.23,1.65)
Hospital Status: Urban (Reference)						
Rural	0.60^{c}	(0.232,1.54)	2.34	(1.96,2.8)	3.64	(2.75,4.81)
Teaching Facility Affiliation	0.80^{c}	(0.357,1.782)	1.36	(1.15,1.59)	2.84	(2.13,3.72)
Coronary Bypass of Two Coronary Arteries	0.99^{c}	(0.893,1.096)	1.11^{c}	(0.99,1.24)	1.14^{c}	(0.94,1.36)
Coronary Bypass of Four or More Coronary Arteries	1.06^{c}	(0.893,1.096)	1.03^{c}	(0.87,1.22)	0.83^{c}	(0.63,1.1)
Coronary Bypass of Three Coronary Arteries	1.10^{c}	(0.907,1.229)	1.03^{c}	(0.91,1.17)	1.05^{c}	(0.86,1.28)
Coronary Bypass of One Coronary Artery	1.00^{c}	(0.981,1.227)	0.92^{c}	(0.81,1.05)	0.85^{c}	(0.69,1.04)
Open Replacement of Aortic Valve with Tissue Graft	1.05^{c}	(0.89,1.119)	1.34^{a}	(1.11,1.6)	1.3	(0.99,1.7)
Open Replacement of Aortic Valve	1.21^{c}	(0.897,1.229)	1.32^{a}	(1.07,1.64)	1.90^{c}	(1.4,2.59)
Atrial Fibrillation	1.16	(1,1.467)	1.73	(1.58,1.89)	2.66	(2.31,3.06)
Coronary Atherosclerosis of Native Coronary Artery	0.91^{c}	(1.071,1.259)	0.61	(0.5,0.74)	0.34	(0.26,0.43)
Diabetes mellitus without mention of complication	1.3^{b}	(0.77,1.069)	1.1	(0.72,0.86)	1.14	(0.46,0.61)
Hyperlipidemia	0.97^{c}	(0.842,0.992)	0.91^{b}	(0.84,0.99)	0.63	(0.55,0.72)
Unspecified Essential Hypertension	1.04^{c}	(0.893,1.043)	1.01	(0.7,0.83)	1.26	(0.55,0.73)
Acute Posthemorrhagic Anemia	0.93^{c}	(0.876,1.026)	1.16	(1.06,1.26)	1.55	(1.35,1.79)
Tobacco Use Disorder	0.89^{a}	(0.857,1.013)	1.03^{c}	(0.93,1.14)	1.03^{c}	(0.88,1.22)
Intermediate Coronary Syndrome	1.01^{c}	(0.808,0.971)	1.95	(1.77,2.15)	1.55	(1.3,1.85)
Acute Myocardial Infarction, Subendocardial Infarction	1.1	(0.918,1.103)	3.53	(3.16,3.95)	4.39	(3.76,5.14)
Congestive Heart Failure	1.09^{c}	(0.765,0.923)	1.74	(1.54,1.96)	3.05	(2.6,3.57)