Preventable Readmission Risk Factors for Patients With Chronic Conditions

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Abstract: Evidence indicates that the largest volume of hospital readmissions occurs among patients with preexisting chronic conditions. Identifying these patients can improve the way hospital care is delivered and prioritize the allocation of interventions. In this retrospective study, we identify factors associated with readmission within 30 days based on claims and administrative data of nine hospitals from 2005 to 2012. We present a data inclusion and exclusion criteria to identify potentially preventable readmissions. Multivariate logistic regression models and a Cox proportional hazards extension are used to estimate the readmission risk for 4 chronic conditions (congestive heart failure [CHF], chronic obstructive pulmonary disease [COPD], acute myocardial infarction, and type 2 diabetes) and pneumonia, known to be related to high readmission rates. Accumulated number of admissions and discharge disposition were identified to be significant factors across most disease groups. Larger odds of readmission were associated with higher severity index for CHF and COPD patients. Different chronic conditions are associated with different patient and case severity factors, suggesting that further studies in readmission should consider studying conditions separately.

Keywords
rehospitalization
machine learning
risk factors
logistic regression
proportional hazard model

Introduction

The U.S. Federal Government is seeking to eliminate unnecessary care and to control growing spending by Medicare that reached $556 billion in 2012 (Rau, 2012). Readmission rates have been established as hospital performance measures with the objective of promoting quality, patient-centeredness, and accountability (CMS, 2013). Readmissions are a costly element of Medicare spending. Almost one fifth of the 11,855,702 Medicare beneficiaries who had been discharged from a hospital were readmitted within 30 days, and 34% were hospitalized within 90 days of which only 10% were likely to have been planned (Jencks et al., 2009). Moreover, the cost of readmissions is estimated at $26 billion annually for Medicare only, and $17 billion of it are potentially preventable (Robert Wood Johnson Foundation, 2013).

A hospital readmission can be defined as an admission to a hospital within a finite time frame after an original admission and discharge. A readmission can occur at either the same hospital or a different hospital, and it can involve planned or unplanned surgical or medical treatments (Stone and Hoffman, 2010). In general, preventable readmissions can be divided into three broad categories: complications or infections arising directly from the initial hospital stay, poorly managed transitions during discharge, and readmissions due to a chronic condition (Center for Healthcare Quality and Payment Reform, 2011).

The largest volume of readmissions occurs among patients with chronic conditions (Stone and Hoffman, 2010). According to Stone and Hoffman (2010), a number of factors might be contributing to this relatively high readmission rate: poor discharge planning and follow-up, low care instructions compliance, inadequate family support, disease complications, and medical errors. Thus, this study assesses readmission risk by chronic condition group to identify and compare significant factors associated with readmission.

There is still much that is unknown about which patient and hospital factors result in a higher probability of a hospital readmission. Hospital-based studies provide opportunities to identify these patients and improve the way hospital care is delivered (Center for Healthcare Quality and Payment Reform, 2011). Identifying the significant factors can help in the creation and implementation of interventions to target these specific conditions and high-risk patient groups.

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Literature Review

There is no standard definition of readmission in the literature. Kansagara and colleagues (2011) conducted a systematic literature review on risk prediction models for hospital readmissions. From this review, differences in the definition of readmissions are identified: the readmission time window (from 15 days to 12 months), type of hospital visit (all-included, potentially preventable, planned, or unplanned), source of data collection (administrative data, prospective clinical data collection, or real-time data collection), population and setting (age range, Medicare, Medicaid, 1 or multiple hospital networks, and departments within the hospital), and the medical condition under study. Although the definition of readmission varies across studies in the literature, most study analyses are driven by policy and decisions at the government level. The Centers for Medicare and Medicaid Services (CMS) annually defines and calculates 30-day readmission rates based on claims and administrative data for public reporting for acute myocardial infarction (AMI), heart failure (HF), and for pneumonia (CMS, 2013).

A number of studies measure readmission rates for specific medical conditions. Congestive heart failure (CHF) (Hamner and Ellison, 2005; Keenan et al., 2008; Kosiborod et al., 2003; Rosati et al., 1991), AMI, chronic obstructive pulmonary disease (COPD), pneumonia (Lindenauer et al., 2010), and type 2 diabetes are the most common diseases studied in readmissions models. However, other disease-specific readmission analyses include cancer (Greenblatt et al., 2010; Reddy et al., 2009) and sickle cell disease (Sobota et al., 2010; Frei-jones and Field, 2009). Studying readmissions and patients by disease group allows studies to use a more homogeneous cohort and implementation of interventions to reduce readmissions.

Logistic regression (LR) is the most commonly used classification technique in readmission research (Allaudeen et al., 2011; Bahadori et al., 2009; Berman et al., 2011; Callaly et al., 2010; Feudtner et al., 2009; Lindenauer et al., 2011; Nantsupawat et al., 2012; Neupane et al., 2010; Whitlock et al., 2010). A major reason for the widespread use of LR is its ease to adjust for different sampling schemes. Cox proportional regression models have also been implemented to assess the risk over time with the proportional hazards assumption. This method is able to identify statistically significant factors related to readmission and high-risk population groups (Capelastegui et al., 2009; Lau et al., 2001; Lipska et al., 2010), although they are limited in their ability to establish either cause and effect or the actual importance of these factors. Studies use both LR and Cox proportional regression models to find significant factors affecting readmission (Belfort et al., 2010; Khawaja et al., 2012; Strouse et al., 2008). Moreover, other studies (Alkalay et al., 2010; Bisgaard et al., 2011; Courtney et al., 2009) used univariate statistical analysis and hypothesis testing to identify significant differences between patients that were readmitted versus those that were not readmitted. The results in these models differ in determining which factors are significant. The variability and lack of consistency in the published relationships could be due to a large number of factors, many of which relate to statistical inference and cause–effect inference.

Readmission risk prediction continues to be difficult and current readmission predicting models perform poorly. Among published articles, the highest predicting ability, in terms of the area under the receiver operating characteristic, is 0.80 (Shulan et al., 2013). Limitations identified include the lack of generalizability of the results since most studies are done for a specific cohort of patients (Cline et al., 1998; Fontanella, 2008; Koelling et al., 2005; Rich et al., 1995), and the limitations of administrative data that may reduce the ability to identify predictors due to absence of important clinical information (Curtis et al., 2009; Frei-jones and Field, 2009; Reddy et al., 2009; Tsuchihashi et al., 2001). To provide more generalizable results, a representative sample size, and relevant data, both clinical and administrative data are suggested (Kaben et al., 2008). However, it has been noted that adding additional risk factors has added complexity without improving the predictive power of models (Spiva et al., 2014).

There are still significant opportunities to advance the understanding of the causes and important risk factors associated with readmissions. The identification of high-risk patient groups could foster preventive interventions (Lin et al., 2011; Reddy et al., 2009), an area where predictive modeling could have a major impact. Although much work has been done to determine the most appropriate definition of readmission, our review shows that there is still no consensus on which readmission definition is best. Our definition of readmission is mostly based on the CMS definition of readmission, and the predictive models built presented in this study are used to identify risk factors, but not as a risk adjustment model. Thus, we believe that it makes sense to identify and predict in advance potentially preventable readmissions.

Purpose

The aims of this study are to identify potentially preventable readmissions based on claims and administrative data, to determine significant factors associated with the risk of being readmitted through a multivariate 30-day LR model and an extension of the Cox proportional hazard model with recurrent events, and to compare the effects of patient factors, case severity, and hospital factors associated with readmission across disease groups that are related to readmissions and their costs.

Study Design and Methods

The data used in this retrospective study are extracted from the administrative claims data of nine hospitals geographically localized within three adjacent counties in Florida. The types of hospitals in the study include general, teaching, and specialized hospitals. The initial dataset includes 594,751 patients accounting for 1,093,177 patient discharges from January 2005 through July 2012. The data were processed in three phases:

Phase I: Exclusion Criteria

The data were filtered based on the exclusion criteria in Table 1. This study excluded single events (admissions) or the entire patient record in the database to classify those readmissions that are avoidable and

Table 1. Excluded Single Admissions or Patient Records

Admissions	Patients
The record of the admission (single event) was excluded if it was due to:	The entire patient record was excluded if he/she was:
Continued care in the same hospital due to same-day internal hospital transfer (This was represented as a readmission in the same day in the database)	Discharged to hospice care
Newborn delivery	Diagnosed with cancer: *ICD-9* code "malignant neoplasm" and ongoing cancer treatment
Trauma	Diagnosed with renal disease and ongoing treatment
Rehabilitation	
Outside transfer and discharge planning is performed	
Elopement: leaving without medical advice and/or treatment	
Death and subsequent to death (i.e., organ donation)	

potentially unavoidable. The records excluded are considered to be routine, planned, or unavoidable. After this process, the final dataset has 470,147 patients and 763,289 hospitalizations with a 30.2% elimination rate.

Phase II: Study Cohort by Disease Type

This study focuses on admissions for specific chronic conditions or diseases that are known for high readmissions rates. Using the *International Classification of Diseases, 9th Revision, Clinical Modification* (*ICD-9-CM*), primary diagnosis code was used to identify admissions for CHF (codes 428.*,402.01, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93), COPD (codes 491.0, 491.1, 491.2, 491.20, 491.21, 490, 492, 496), AMI (codes 410.*), type 2 diabetes (codes 250.*2), and pneumonia (codes 480–483, 485–486, 510, 511.0, 511.1, 511.9 and a primary diagnosis of a pneumonia-related symptom [codes 780.6, 780.6, 786.00, 786.05, 786.06, 786.07, 786.2, 786.3, 786.4, 786.5, 786.51, 786.52, 786.7] and a secondary diagnosis of pneumonia, emphysema, or pleurisy) as index admissions for these 5 illnesses.

Phase III: Planned/Unplanned Readmissions

We used the definition of planned/unplanned readmissions stated in the Hospital-Wide All-Cause Unplanned Readmission Measure final report for CMS (Horwitz et al., 2008). Planned readmissions were defined as those in which one of a prespecified list of procedures took place. This analysis considered only unplanned admissions within 30 days as the outcome of interest in the predictive models. This time frame was used to follow the CMS readmission definition standards to estimate high readmission penalties.

Study Variables

The descriptive statistics for the data and variables' categories are shown in Table 2. After discussions with hospital experts, we classified the variables for this study in three categories: (1) "patient factors": age range, gender, marital status, race/ethnicity, and language; (2) "case severity factors": severity of illness (from 1 = *minor* to 4 = *extreme* as defined by 3M APR DRG; 3M Health Information Systems, 2008), behavioral health comorbidities (1 if present as a secondary diagnosis, 0 otherwise), Charlson comorbidity index (Charlson Co; calculated based on the comorbid conditions and severity; Charlson et al., 1994), and length of stay (LOS) (days); (3) "hospital factors": hospitalist (1 if present, 0 otherwise), payer class, discharge disposition, admission type, and year (over seven years).

Analytical Methods

A LR model and a proportional hazard model were used to identify statistically significant variables and assess their 30-day unplanned readmission relative risk and the readmission risk over time (hazard ratio [HR] for recurrent events).

Logistic Regression and 30-Day Readmission Risk. We built a LR model to predict an unplanned readmission within 30 days of discharge as a binary output variable (Y = 1, if readmitted within 30 days, or 0 otherwise). The results are interpreted using the quantity $\log\frac{p}{1-p}$ (the "log odds") to compare the relative risks among the different class levels of the independent variables. Goodness-of-fit is evaluated using the Hosmer–Lemshow statistic and cross-validation. A Wald test is used to test the statistical significance of each coefficient (β) in the model and to create the 0.95 confidence intervals (CIs).

Proportional Hazard Model With Recurrent Events. We applied a Cox proportional hazards extension to estimate effects of covariates which are reported as HRs. The motivation for using proportional hazard model with recurrent events is that 1 patient might

Table 2. **Descriptive Statistics for Study Variables**

	CHF	COPD	AMI	Pneumonia	Type 2 Diabetes
No. of patients	7,287	5,946	9,688	10,897	4,879
No. of admissions	9,590	7,921	11,210	12,130	6,158*
Patient factors					
Age					
18–45	4.83	4.61	6.07	16.62	24.90
45–55	9.76	14.97	16.88	14.64	22.73
55–65	13.54	24.07	23.07	14.95	19.31
65–75	17.02	25.08	19.86	15.34	15.43
75–85	27.82	21.78	21.08	21.73	12.11
85+	14.93	6.19	7.79	9.32	3.73
Null	12.10	3.31	5.25	7.40	1.78
Gender					
Female	51.41	56.93	41.28	55.90	49.97
Male	48.59	43.07	58.72	44.10	50.03
Marital status					
Divorced/Separated	11.29	19.88	10.34	11.83	16.29
Married	39.74	35.89	51.27	41.28	35.85
Single	21.30	23.65	22.75	27.13	35.62
Widowed	27.67	20.59	15.64	19.77	12.24
Race					
Black	15.21	8.98	6.17	11.78	28.28
Hispanic	8.08	4.94	8.26	8.68	12.85
White	75.31	84.86	82.40	77.71	56.94
Other	1.40	1.21	3.17	1.83	1.93
Language					
English	70.22	79.52	78.55	75.19	78.73
Other	29.78	20.48	21.45	24.81	21.27
Case severity factors					
Severity of illness					
1 = Minor	9.35	20.26	25.22	10.84	21.60
2 = Moderate	45.29	43.23	40.95	48.41	33.87
3 = Major	35.33	24.25	22.74	31.55	23.22
4 = Extreme	5.52	3.04	9.05	6.10	3.00
Null	4.52	9.22	2.03	3.10	18.30
Behavioral health comorbidity					
No	76.53	65.24	80.09	70.26	74.76
Yes	23.47	34.76	19.91	29.74	25.24
Charlson comorbidity					
0	15.90	0.00	34.87	28.12	10.02
1	24.59	47.54	31.01	37.00	32.97
2	22.90	26.70	16.76	18.10	18.27
3	15.45	12.08	8.18	7.64	15.61
4	9.69	6.77	4.30	4.43	10.56
5+	11.47	6.91	4.88	4.71	12.59
Length of stay (days)					
Mean (min, max)	4.6 (0, 19)	3.8 (0, 56)	4.1 (0, 78)	5.2 (0, 15)	3.8 (0, 90)

(*Continued*)

Table 2. (*Continued*)

	CHF	COPD	AMI	Pneumonia	Type 2 Diabetes
Hospital factors					
Hospitalist					
Yes	25.85	29.10	27.27	28.62	32.64
No	74.15	70.90	72.73	71.38	67.36
Payer class					
Commercial	9.49	10.96	26.52	18.39	19.96
Medicaid	10.32	14.47	8.26	12.56	21.14
Medicare	75.89	67.44	55.98	60.00	44.71
Other	4.30	7.13	9.24	9.05	14.19
Discharge disposition					
Nonacute facility	43.02	29.57	26.43	33.79	32.49
Routine/home	52.74	67.10	57.22	63.45	64.08
Specialty hospital	2.89	1.00	14.99	0.88	0.99
Other	1.35	2.34	1.36	1.88	2.44
Admission type					
Emergency	83.67	82.07	77.25	87.36	69.29
Routine	4.53	9.22	2.08	3.10	18.32
Urgent	6.61	3.64	9.22	4.23	5.31
Other	5.19	5.08	11.45	5.31	7.08
No of previous admissions					
Mean (min, max)	2.8 (1, 36)	3.3 (1, 45)	1.9 (1, 49)	2.4 (1, 59)	3.1 (1, 52)
Year					
H	19.26	13.26	14.89	16.07	14.31
I	16.03	12.11	13.31	14.55	13.41
J	13.23	12.02	15.58	13.72	13.30
K	13.69	14.76	16.33	14.06	14.70
L	12.40	17.04	14.99	15.00	15.54
M	14.58	17.28	14.59	15.42	15.85
N–O	10.81	13.53	10.31	11.19	12.89

*Includes 55 patients who are younger than 18 years.
AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

have multiple records of admission during the seven years of data. Also, data might be heterogeneous across individuals and event dependent. Several survival models of recurrent events have been extended based on semiparametric Cox proportional hazard models (Gjessing et al., 2010). Based on the special features of the readmission problem, a conditional frailty model that combines a random effect with stratification of events is recommended (Box-Steffensmeier and De Boef, 2006). The model assumes that the contributions to the k^{th} admission are restricted to only those patients who have previously experienced the $k-1^{th}$ admission. The hazard of k^{th} event occurring for the i^{th} subject is

$$\lambda_{ik}(t; Z_{ik}) = \lambda_{0k}(t - t_{k-1})e^{\beta' Z_{ik}(x_{ik}) + \omega_i}, \quad (1)$$

where X_{ik} and Z_{ik}, respectively, denote the observation time and covariate vector for the i^{th} subject with respect to the k^{th} event, and β is the unknown regression parameter vector. λ_{0k} is the baseline hazard rate and $(t - t_{k-1})$ represents the gap time between k^{th} and $k-1^{th}$ events. ω_i is the vector of random effects (frailties) across events.

Institutional Review Board Approval

This project was formally exempted by the University of South Florida Institutional Review Board because it does not meet the definition of human subjects research.

Results

The LR model and the conditional frailty proportional hazard model were built in SAS (version 9.3) and R (version 3.0.2), respectively. In the LR modeling predicting the 30-day risk of readmission, statistically significant variables are selected using a stepwise selection (entry = 0.10, stay = 0.10) removing insignificant variable from the model before adding a significant variable to the model in every step. For the proportional hazard model, variables are selected based on the level of statistical significance ($P \leq .10$) as well.

The statistically significant factors ($P \leq .05$) in the prediction of readmission varied across disease groups and prediction models, especially for patient and case severity factors. A large amount of hospital factors were found to be statistically significant ($P \leq .05$) in both models and across all diseases: accumulated number of admissions, year, and discharge disposition. The presence of a hospitalist and the discharge day of week were not found statistically significant in any of the models. The list of statistically significant factors found in each model across disease groups and the performance for the LR model, in terms of its discriminatory power (c-statistic), is presented in Table 3. The relative risks for the predictors' class levels are analyzed using the odds ratio (OR) from the LR model and the HR from the proportional hazard model. The OR and HR estimates are expressed as a ratio point estimate and the 0.95 CI upper and lower limits in Table 4.

Hospital Factors

The higher the accumulated times a patient has been readmitted to the hospital (OR from 1.06 to 1.15), the more likely it is that this person will be readmitted within 30 days. The OR and HR showed a consistent decreasing trend in readmission risk over the years in the data analyzed. Discharge disposition to another acute hospital or specialty hospital has the higher odds of being readmitted among other dispositions (routine home, nonacute facility, or other). Payer class was identified as significant for CHF, COPD, pneumonia, and type 2 diabetes. In most of the cases, patients with Medicaid and Medicare had the higher ratio (OR) of readmission among the payer classifications (commercial insurance). The type admission for the patient is considered for CHF, AMI, and type 2 diabetes; moreover, patients admitted as emergency have higher odds of readmission.

Case Severity Factors

Length of stay was statistically significant in across all disease groups, except for AMI. The more days the patient has stayed in the hospitals, the higher the likelihood of being readmitted with 30 days and risk of readmission over time. The proportional hazard model identified the Charlson comorbidity index as a significant factor in patients with CHF, AMI, Pneumonia and Type 2 Diabetes; moreover, patients with an index of 3 or higher have the highest odds of readmission HR over time (OR are also higher in this range for pneumonia and type 2 diabetes). Severity of illness index was included in one or both models for CHF, COPD, and pneumonia, and the odds of readmission increases as severity index is higher. Having a comorbidity related to a behavioral health condition was found for CHF patients, and the probability of readmission for having this comorbidity is 1.18 times higher than not having it.

Patient Factors

The differences of significant factors differed drastically across disease groups. The LR model found age to be significant only in the type 2 diabetes cohort. However, the proportional HR found it significant in four of the five disease groups. Gender was only included in the proportional hazard model, with higher HR for female patients.

Table 3. Significant Factors in Prediction Models

	CHF		COPD		AMI		Pneumonia		Type 2 Diabetes	
	30-Day Risk $c = 0.63$	Hazard Ratio	30-Day Risk $c = 0.68$	Hazard Ratio	30-Day Risk $c = 0.74$	Hazard Ratio	30-Day Risk $c = 0.67$	Hazard Ratio	30-Day Risk $c = 0.73$	Hazard Ratio
Patient factors										
Age		x		x				x	x	x
Language	x	x	x		x	x				
Marital status				x	x		x		x	
Race		x					x			x
Gender						x				
Case severity factors										
Behavioral health	x									
Severity of illness	x		x	x			x	x		
Length of stay	x		x	x			x	x	x	x
Charlson comorbidity		x				x	x	x	x	x
Hospital factors										
Hospitalist*										
Discharge day of week*										
Admission type		x			x				x	
Payer class		x	x	x			x	x		x
No. of previous admissions	x	x	x	x	x	x	x	x	x	x
Year	x	x	x	x	x	x	x	x	x	x
Discharge disposition	x	x	x	x	x	x	x	x	x	x

*Variable was not found significant by either model for the disease groups studied. It will not be included in the analysis of results.

AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

Discussion

The objective of this study was to further understand the risk factors associated with unplanned readmissions within 30 days in prespecified disease cohorts. Using two predictive modeling techniques, we were able to identify and compare factors associated with the patient, hospital stay, and disease case severity.

Both the LR model and the proportional hazards model for 30-day readmission generate a different mix of significant risk factors in all five diseases. Thus, we performed analyses for readmission for specific diseases to better understand specific factors of a given disease. In most cases, factors were consistent across the specified diseases. For example, patients with commercial insurance always have lower risk of being readmitted, and longer LOS is associated with a higher probability of readmission. We found common significant factors across

Table 4. Model Parameter Relative Risks

	CHF		COPD	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Patient factors				
Age				
18–45		1		1
45–55		0.94 (0.77–1.15)		1.52 (1.18–1.97)
55–65		0.78 (0.64–0.96)		1.6 (1.25–2.06)
65–75		0.73 (0.59–0.9)		1.46 (1.12–1.91)
75–85		0.78 (0.63–0.96)		1.27 (0.97–1.68)
85+		0.81 (0.65–1.01)		1.35 (0.98–1.85)
Gender				
Female				
Male				
Marital status				
Divorced				1
Married				0.84 (0.75–0.95)
Single				0.93 (0.82–1.05)
Widowed				0.98 (0.86–1.13)
Race				
Black		1		
Hispanic		0.86 (0.73–1.02)		
White		0.81 (0.73–0.91)		
Other		0.57 (0.38–0.85)		
Language				
English	1	1	1	
Other	1.17 (0.99–1.38)	1.13 (1–1.27)	1.27 (1.01–1.6)	
Case severity factors				
Disease severity				
1	1		1	1
2	1.23 (0.99–1.52)		1.17 (0.97–1.41)	0.99 (0.88–1.1)
3	1.32 (1.06–1.66)		1.39 (1.13–1.72)	1 (0.88–1.14)
4	1.33 (0.97–1.85)		1.62 (1.09–2.41)	0.94 (0.71–1.24)
Behavioral health comorbidity				
0	1			
1	1.18 (1.04–1.34)			

(Continued)

Table 4. (Continued)

	CHF		COPD	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Charlson comorbidity				
0		1		
1		1.14 (0.99–1.3)		
2		1.22 (1.06–1.39)		
3		1.3 (1.12–1.51)		
4		1.34 (1.14–1.59)		
5+		1.26 (1.06–1.49)		
Length of stay (days)	1.02 (1–1.03)		1.04 (1.02–1.06)	1.03 (1.02–1.04)
Hospital factors				
Payer class				
Commercial		1	1	1
Medicaid		1.36 (1.14–1.62)	1.94 (1.45–2.6)	1.56 (1.3–1.87)
Medicare		1.23 (1.04–1.46)	1.44 (1.11–1.88)	1.38 (1.16–1.64)
Other		0.87 (0.68–1.11)	1.55 (1.09–2.22)	1.48 (1.19–1.84)
Accumulated number of admissions	1.15 (1.12–1.17)	1.08 (1.07–1.1)	1.15 (1.13–1.17)	1.09 (1.08–1.1)
Discharge disposition				
Nonacute facility	1	1	1	1
Routine/home	0.83 (0.73–0.93)	1.05 (0.96–1.15)	0.9 (0.77–1.05)	1.04 (0.94–1.16)
Specialty hospital	2.43 (1.85–3.2)	1.74 (1.4–2.17)	2.13 (1.27–3.58)	1.45 (0.98–2.15)
Other	1.59 (1.04–2.44)	1.27 (0.93–1.72)	1.78 (1.21–2.62)	1.58 (1.21–2.06)
Admission type				
Emergency		1		
Other		0.8 (0.65–0.99)		
Routine		0.83 (0.7–0.98)		
Urgent		0.87 (0.73–1.04)		
Year				
1	1	1	1	1
2	0.88 (0.73–1.06)	0.86 (0.76–0.97)	0.96 (0.75–1.23)	0.91 (0.78–1.06)
3	0.77 (0.61–0.97)	0.83 (0.71–0.97)	0.88 (0.65–1.2)	0.84 (0.72–0.98)
4	0.84 (0.66–1.05)	0.84 (0.71–0.98)	0.85 (0.63–1.15)	0.79 (0.68–0.91)
5	0.72 (0.57–0.92)	0.7 (0.6–0.83)	0.78 (0.58–1.04)	0.69 (0.6–0.81)
6	0.76 (0.6–0.96)	0.74 (0.63–0.87)	0.72 (0.53–0.97)	0.62 (0.53–0.72)
7–8	0.57 (0.44–0.74)	0.43 (0.35–0.52)	0.54 (0.39–0.75)	0.3 (0.25–0.37)

(Continued)

Table 4. (*Continued*)

	AMI		Pneumonia		Type II Diabetes	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Patient factors						
Age						
18–45				1	1	1
45–55				1.07 (0.89–1.27)	1.8 (0.55–5.87)	1.01 (0.84–1.21)
55–65				1.03 (0.86–1.23)	1.03 (0.31–3.4)	0.68 (0.55–0.84)
65–75				0.84 (0.68–1.03)	1.52 (0.46–5.05)	0.67 (0.51–0.88)
75–85				0.79 (0.65–0.97)	1.8 (0.54–6)	0.73 (0.55–0.97)
85+				0.83 (0.66–1.05)	2.11 (0.61–7.37)	0.65 (0.43–0.98)
Gender						
Female		1				
Male		0.89 (0.79–1.01)				
Marital status						
Divorced	1		1		1	
Married	1.13 (0.95–1.36)		0.77 (0.64–0.92)		0.82 (0.65–1.03)	
Single	0.92 (0.75–1.12)		0.85 (0.7–1.03)		0.91 (0.72–1.14)	
Widowed	1.12 (0.91–1.39)		0.72 (0.59–0.89)		0.62 (0.44–0.87)	
Race						
Black			1			1
Hispanic			0.79 (0.6–1.04)			0.8 (0.64–1.01)
White			1.03 (0.85–1.24)			0.61 (0.34–1.08)
Other			0.85 (0.51–1.39)			0.95 (0.81–1.1)
Language						
English	1	1				
Other	1.19 (1.02–1.4)	1.13 (0.95–1.34)				
Case severity factors						
Disease severity						
1			1	1		
2			1.09 (0.86–1.39)	1.2 (0.99–1.45)		
3			1.32 (1.03–1.7)	1.36 (1.11–1.65)		
4			1.55 (1.12–2.16)	1.35 (1.04–1.77)		
Behavioral health comorbidity						
0						
1						

(*Continued*)

Table 4. (Continued)

	AMI		Pneumonia		Type II Diabetes	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Charlson comorbidity						
0		1	1	1	1	1
1		1.03 (0.9–1.19)	1.16 (0.98–1.36)	1.26 (1.1–1.44)	0.9 (0.62–1.3)	0.95 (0.73–1.24)
2		1.01 (0.85–1.19)	1.27 (1.05–1.53)	1.37 (1.18–1.6)	1.73 (1.19–2.5)	1.58 (1.2–2.07)
3		1.13 (0.9–1.42)	1.4 (1.11–1.77)	1.47 (1.22–1.78)	2.01 (1.38–2.91)	1.74 (1.32–2.29)
4		1.35 (1.03–1.78)	1.57 (1.2–2.06)	1.5 (1.2–1.89)	1.9 (1.28–2.83)	1.96 (1.46–2.63)
5+		1.03 (0.77–1.39)	1.55 (1.19–2.02)	1.56 (1.25–1.94)	1.87 (1.25–2.78)	1.67 (1.23–2.26)
Length of stay (days)			1.02 (1–1.03)	1.01 (1.01–1.02)	1.03 (1.01–1.04)	1.03 (1.02–1.04)
Hospital factors						
Payer class						
Commercial			1	1		1
Medicaid			1.6 (1.26–2.02)	1.73 (1.44–2.08)		1.51 (1.23–1.85)
Medicare			1.47 (1.21–1.78)	1.79 (1.5–2.14)		1.31 (1.06–1.63)
Other			1.02 (0.76–1.37)	1.02 (0.81–1.28)		1.07 (0.85–1.35)
Accumulated number of admissions	1.12 (1.09–1.15)	1.14 (1.09–1.18)	1.09 (1.07–1.11)	1.06 (1.05–1.08)	1.11 (1.09–1.12)	
Discharge disposition						
Nonacute facility	1	1	1	1	1	1
Routine/home	0.6 (0.52–0.69)	0.74 (0.65–0.85)	0.72 (0.62–0.82)	0.83 (0.74–0.93)	0.88 (0.72–1.07)	1.52 (1.09–2.1)
Specialty hospital	6.74 (5.82–7.81)	41.1 (33.99–49.7)	3.26 (2.14–4.97)	2.9 (1.98–4.26)	3.95 (2.21–7.04)	0.92 (0.8–1.07)
Other	1.1 (0.71–1.72)	1.36 (0.86–2.16)	1.62 (1.12–2.35)	1.55 (1.13–2.11)	2.15 (1.41–3.29)	3.35 (1.92–5.85)
Admission type						
Emergency	1				1	
Other	1.1 (0.78–1.55)				0.8 (0.62–1.04)	
Routine	0.73 (0.58–0.9)				0.9 (0.63–1.27)	
Urgent	0.84 (0.69–1.01)				0.73 (0.52–1.03)	
Year						
1	1	1	1	1	1	1
2	0.85 (0.7–1.04)	0.86 (0.7–1.06)	0.96 (0.78–1.17)	1.01 (0.87–1.18)	0.73 (0.55–0.98)	0.68 (0.55–0.84)
3	1 (0.81–1.24)	0.9 (0.71–1.13)	0.89 (0.72–1.1)	0.89 (0.76–1.04)	0.65 (0.48–0.87)	0.83 (0.67–1.02)
4	0.85 (0.69–1.06)	0.8 (0.64–1.01)	0.91 (0.74–1.12)	0.95 (0.81–1.11)	0.63 (0.47–0.84)	0.71 (0.57–0.87)
5	0.91 (0.73–1.14)	0.76 (0.6–0.96)	0.76 (0.61–0.93)	0.77 (0.65–0.91)	0.59 (0.44–0.79)	0.59 (0.48–0.73)
6	0.74 (0.59–0.93)	0.66 (0.51–0.84)	0.76 (0.62–0.94)	0.74 (0.62–0.87)	0.51 (0.38–0.69)	0.52 (0.41–0.65)
7–8	0.73 (0.57–0.94)	0.56 (0.43–0.75)	0.7 (0.55–0.88)	0.56 (0.45–0.68)	0.48 (0.35–0.66)	0.39 (0.3–0.51)

Ratio values are expressed as point estimate (0.95 confidence interval).
AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

diseases: discharge disposition, Charlson comorbidity index, and number of previous admissions.

Interesting patterns are found for some factors. For instance, as LOS increases, risk of readmission increases. For a large number of potential factors (i.e., case severity), LOS can be a surrogate measure. In the scope of this study, we cannot explain this behavior, and more clinical information is needed to understand potential causation. People speaking languages other than English have higher risk of readmission. In the literature, it has been found that discharge instructions are important in the reduction of readmissions, and one can hypothesize that patients who do not speak English need better means of communication for their discharge instructions. In the case of the patients' age, different risk patterns are observed across diseases. For type 2 diabetes patients, younger to middle-aged patients have higher readmission risk than elderly patients. However, COPD patients between the ages of 45 and 65 years have higher risk than others.

Most of the significant variables found are reasonable. However, some results need further investigation. For example, for hospital factors, is payer class difference due to the socioeconomic status or the hospital systems? Commercial insurance holders have a lower chance of being readmitted compared with all other payer classes. Moreover, another study also found that commercial insurance holders to have lower odds of readmissions compared with Medicare and Medicaid (Kruse et al., 2013), and this might be due to common characteristics that a patient in this group share (e.g., age, healthy enough to be employed, and income). Payer class can be an estimator of the socioeconomic situation of the patients admitted. We also find that older patients have a lower chance to be readmitted in the case of CHF. One study (Kosiborod et al., 2003) shows that the use of transfusions or other treatments for patients with anemia aged 65 years or older with HF could be the reason for lower readmission rate. However, our study lacks information of treatment during the stay.

Limitations

Our study provides important insights into the hospital readmission problem based on a network of hospitals located in Florida over 7 years of data and patients older than 18 years. However, there are several limitations in our study. First, our dataset comes from the administrative data collected that does not contain complete clinical information for the admission. These hospitals are located in the same extended metropolitan area, which means that the study population cannot be generalized to other areas in the country. The unavailability of clinical records and medical tests limits our ability to evaluate other variables that may be more closely related to how the patient was treated during a hospital stay. We believe that lack of patient transfer and discharge information also hinders tracking patients' visits to other facilities outside the network. Finally, model performance was modest in terms of the *c*-statistic achieved by the models (c-statistics between 0.63 and 0.74), but this performance is comparable with current predictive models in the literature (Kansagara et al., 2011; Kruse et al., 2013).

Directions for Future Research

In future studies, predictive models should explore the addition of other clinical factors associated with the patient visit to the hospital. This might enhance the identification of risk factors beyond the administrative claims data. To improve accuracy and discriminatory power of predictive models, other machine learning tools can be used to exploit more data complexity (i.e., decision trees, random forest, and support vector machine). In the practice, this study suggests that hospital further evaluates potential interventions for specific patient population at higher risk of readmission. However, interventions are already being designed to address specific needs such as patient education and discharge protocols (Koelling et al., 2005; Manning, 2011; Younis et al., 2012), analysis of racial disparities to reduce readmission rates for a specific population (Joynt et al., 2011), and the impact of specific medical intervention pertinent to a given disease to reduce mortality and readmission rates (Curtis et al., 2009). Finally, to capture patient characteristics more precisely, competing risk models for the interactions, one, two, or more diseases can also be studied, since a large number of patients with disease combination could be at risk for all potential diseases.

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