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Predicting Future Hospital Admissions:
Can We Focus Intensive Readmission Avoidance Efforts More Effectively?

Adam Hobgood, MS, Huiwen Zeng, PhD, Jay Chyung, MD, PhD

ABSTRACT

Readmission to the hospital after discharge represents a cause of distress for patients and significant unnecessary cost to the health care system. Although better hospital care transitions with follow-up support for the discharge plan and general health management are proven approaches to decrease readmission rates, identifying the admitted patients in greatest need of additional post-discharge support is a challenge. Healthways developed and evaluated two predictive models to identify patients at risk of readmission within 30 days of discharge among a population diverse with respect to age, gender and diagnosis.

Both predictive models generate a readmissions risk index (RRI), a score that represents an individual's relative risk of 30-day readmission based on a variety of variables associated with this outcome. One model incorporates both a patient's historical (prior year's claims) and current health care data (hcRRI). The other uses a patient's current health care data alone (cRRI), built from claims data that replicate data also available to health care providers during an admission, for use in settings in which historical claims are unavailable. A split-sample design was implemented to derive and validate the risk index in a commercially insured population. The hcRRI model yielded slightly higher discriminatory power than the cRRI model. Among patients admitted between June 2008 and May 2009 and who were assigned by each model to a 25% cohort with the highest risk among all admissions, the hcRRI captured 45% of all actual 30-day readmissions and the cRRI captured 44%, both nearly doubling the rate as identified by chance in the general population.

Both models represent useful tools to direct programs aimed at reducing readmissions through personalized interventions and each may be uniquely applicable to different settings based on the data availability. A primary advantage of using these models in the clinic or for managing the health of a larger population is to allow readmission-avoidance programs to be delivered at scale in a cost-effective manner. Identifying patients at highest risk for readmission allows care teams to direct limited resources most efficiently for the purpose of reducing 30-day readmissions. Effective programs guided by these models represent a significant step toward improving quality of care and containing healthcare costs.

INTRODUCTION

Readmission to the hospital for any reason within 30 days of discharge represents a setback to patients, caregivers and quality overseers, and is a source of significant cost to health insurers. Of insured adult patients who are admitted to the hospital, 11.3% are readmitted within 30 days. This number increases further among the uninsured and Medicare beneficiaries, with rates of 12.9% and 19.0% respectively.[1] Readmission costs are typically 30% to 40% higher than the average expense of acute hospitalizations.[2] The Medicare Payment Advisory Commission estimates that the U.S. government spends $12 billion annually on "potentially preventable readmissions" for Medicare alone.[3] Jencks et al put the cost to Medicare of unplanned rehospitalizations even higher – $17.4 billion in 2004.[4] Thus, readmission represents an important target for health care cost containment.

Due to the prevalence and cost of preventable readmissions, this area has become a focus for quality improvement efforts. Recent changes in policy and practice are intended to provide external motivation for such quality improvement. For example, in 2009 the Centers for Medicare & Medicaid Services began posting 30-day readmission rates for patients admitted for heart failure (HF), acute myocardial infarction (AMI) and pneumonia on its Hospital Compare website (www.hospitalcompare.hhs.gov). With public scrutiny as one driver of improvement, an even more direct repercussion ensued with passage of the Patient Protection and Affordable Care Act in 2010 (P.L. 111-148). Through this legislation, CMS will begin holding hospitals accountable for their readmission rates and adjusting payments to hospitals in 2013 according to their rate of "excess" vs "expected" Medicare readmissions for pneumonia, AMI, and HF.[5, 6]

Direct correspondence to: Center For Health Research
Healthways, Inc.
701 Cool Springs Blvd.
Franklin, TN 37067 USA
research@healthways.com

But at a time when cost effectiveness is paramount, there is opportunity to implement scalable care transition and readmission avoidance programs by delivering individual interventions selectively to patients at the highest risk of discharge. Prior research has provided data to indicate that certain traits and care-related variables are associated with higher readmission rates. Examples include older age, gender, race, diagnosis, comorbidity, Medicaid coverage, and the length of stay during the index admission.[7] Readmission rates also vary by hospital, state, and geographic region.[8] However, less is known about these and other risk-related patient characteristics work in concert to affect an individual's overall risk. Predictive models have been developed for this purpose, but have typically focused on a specific population, such as seniors, limiting broad applicability, and have demonstrated varying degrees of accuracy (Kansagara, 2011).[9] A reliable and generalizable tool to predict the patients most likely to be readmitted would represent a foundational piece of a new generation of programs designed to more broadly impact readmission rates.

The purpose of this study was to develop and test two predictive models to identify patients at risk for readmission that would be applicable in different settings based on the available patient data. The cRRI was developed using "current" health care records, using data from the first day of a hospitalization as well as the period immediately preceding an admission, as would be available in a hospital setting. The hcRRI was developed using both the current data and historical claims data and would be applicable when complete claims data are available for the year prior to an admission. The models were intended to provide a valid and accurate tool to improve outcomes from programs intended to improve quality through reduced readmissions.

METHODS

Using claims data from a major U.S. health care insurer, we extracted data from 22,920 hospitalizations occurring between June 2008 and May 2009 to evaluate readmission rates and to develop a model to predict readmission within 30 days of discharge. Additionally we examined data in June 2009 as necessary to establish 30-day readmission status for hospitalizations at the end of the study year. We considered planned and unplanned readmission for all causes, with the exception of chemotherapy and pregnancy, not limiting the focus to readmissions stemming from the cause of the index hospitalization. The criteria were similar to those used by Jencks et al in their seminal 2009 paper.[4]

As a descriptive analysis of readmissions in our population, we evaluated the rate of readmissions in 7-day increments for the 30 and 90 day periods following hospital discharge. 30-day readmissions were evaluated based on the 22,920 hospitalizations occurring from June 2008 to May 2009. Ninety-day readmissions were evaluated using the 19,240 hospitalizations occurring from June 2008 to March 2009. Different timeframes were used as a necessity to allow us to examine the full post-discharge readmission periods within our study data (inclusive of potential readmissions in June 2009).

In developing the Readmission Risk Index using current data (cRRI model), approximately 100 variables were extracted from claims data to simulate information available in the hospital environment. In addition to the variables used in the cRRI, another 200 claims-based independent variables, extracted from the prior year of claims history (June 2007-May 2008), were used to create the model built using both historical and current data (hcRRI).

TABLE 1: DEMOGRAPHICS OF HOSPITALIZED PATIENTS UNDER STUDY.

Variable	N	%*
Hospitalizations	22920	
(Unique Persons)	(17689)	
Readmissions	2019	8.81%
Female	9138	51.66%
Age		
18-39 yrs	4026	22.76%
40-54 yrs	6692	37.83%
55-64 yrs	6268	35.42%
≥ 65 yrs	703	3.97%
Average	*48.7*	
Utilization		
ER Visits	9505	41.47%
ICU	3957	17.26%
Surgery	11014	48.05%
Average LOS	*5.0*	
Disease		
Asthma	226	0.99%
Depression	1958	8.54%
CHF	935	4.08%
CAD	2726	11.89%
COPD	945	4.12%
Diabetes	235	1.03%
Medication		
Antidepressant	4803	20.96%
Diuretic	1247	5.44%
ACE Inhibitor	2583	11.27%
ARB	1102	4.81%
Beta Blocker	3588	15.65%
Warfarin	1855	8.09%
Avg # Drug Classes	*2.8*	

* All percentage results for the variables presented in the table used the number of hospitalizations as denominator, with the exception of gender and age.

ER, emergency room; ICU, intensive care unit; LOS, Length of stay; CHF, congestive heart failure; CAD, coronary artery disease; COPD, chronic obstructive pulmonary disease; ACE, angiotensin converting enzyme; ARB, angiotensin receptor blocker

Categories of variables considered for RRI models:

- Factors related to diseases and conditions (CHF, CAD, pneumonia)
- Factors related to hospital-based activity (ICU stay, ambulance transportation)
- Factors related to medication therapy (usage at therapeutic class and individual therapy levels)
- Financial factors (total costs, costs by place of service)
- Procedure-based factors (condition-specific procedures, total procedures)
- Demographic factors (age, gender)
- Other factors summarizing ER, inpatient, physician, pharmacy, outpatient and home health utilization

The models underwent a development and validation process in which half of the hospitalization events were randomly chosen as training data to derive the RRI models and remaining data was used to validate the models. Such a split-sample design tests whether the analytical performance of the model is consistent across the entire study population.

All variables from 'current' data set were tested for multicollinearity and a subset was chosen comprising candidate variables that were included in stepwise logistic regression models. Multivariate logistic regression measured the associations of these variables with 30-day readmission. Stepwise selection was conducted with an inclusion criterion of $p \leq 0.05$ to include only significant variables in the final logistic models for the cRRI. The same process was employed in developing the hcRRI, but expanding the set of variables to include those from the historical data set.

The final cRRI and hcRRI model performance was evaluated in the validation data set by comparing predicted 30-day readmissions, based on varying thresholds of index scores, to the actual proportion of 30-day readmissions captured within that risk threshold. Predictive power was quantified using receiver operating characteristic (ROC) c-statistic.

RESULTS

Characterization of Readmissions

To learn the extent of the readmission problem, we determined, in 7-day increments, the rate of readmissions within 30 or 90 days from discharge (Table 2). Among 30-day readmissions, which occurred at an overall rate of 8.8%, 64.78% of these occurred within two weeks of discharge. Of 90 day readmissions, nearly 60% occurred within the first 4 weeks. These results demonstrate the significant problem with readmissions in general, and the need to specifically focus on 30-day readmissions given the significant opportunity here. To understand the scope of the 30-day readmissions problem with respect to all admissions, we compared the numbers over an entire year and found that 8.8% of all hospitalizations were 30-day readmissions.

Evaluation of readmissions by patient diagnosis, irrespective of the cause of the readmission, found that CHF, COPD and pneumonia were most frequently associated with 30-day readmission. The rates of readmission for these diagnoses are shown in Table 4.

Model Validation

The two developed models, hcRRI and cRRI, were evaluated for their ability to predict readmissions that actually occurred. Table 3 shows the performance of the two models using hospitalization cohorts selected from the entire study sample that ranged in size from 0% to 50% of the full sample. The cohorts selected from the sample by each of the models represented the

TABLE 2: OCCURRENCE OF READMISSION WITHIN 30 AND 90 DAYS OF DISCHARGE.

Week	30-day readmissions[1]			90-day readmissions[2]		
	Number of Readmissions	% of total 30-day readmissions	% of total hospitalizations	Number of Readmissions	% of total 90-day readmissions	% of total hospitalizations
1st	836	41.41%	3.65%	729	24.33%	3.79%
2nd	472	23.38%	2.06%	415	13.85%	2.16%
3rd	359	17.78%	1.57%	325	10.855%	1.69%
4th	286	14.17%	1.24%	251	8.38%	1.30%
5-6th				417	13.92%	2.17%
7-8th				323	10.78%	1.68%
9-10th				250	8.34%	1.30%
11-12th				212	7.08%	1.10%

[1] Based on 22,920 hospitalizations that occurred between June 2008 and May 2009.

[2] Based on 19,240 hospitalizations that occurred between June 2008 and March 2009.

TABLE 3: READMISSION CAPTURE BY cRRI AND hcRRI MODELS COMPARED TO CHANCE AT VARIOUS COHORT SIZES.

		cRRI Selected Cohorts			hcRRI Selected Cohorts			Chance Selection*		
Cohort Size	Admissions, N	Readmissions Captured, N	Readmission Rate (CI)	Capture Rate	Readmissions Captured, N	Readmission Rate (CI)	Capture Rate	Readmissions Captured, N	Readmission Rate	Capture Rate
20.0%	4584	773	16.86% (±0.55%)	38.28%	813	17.73% (±0.56%)	40.25%	403	8.8%	20%
25.0%	5730	896	15.64% (±0.48%)	44.40%	917	16.01% (±0.48%)	45.44%	504	8.8%	25%
30.0%	6876	1016	14.77% (±0.43%)	50.31%	1045	15.20% (±0.43%)	51.76%	605	8.8%	30%
35.0%	8022	1129	14.07% (±0.39%)	55.91%	1154	14.39% (±0.39%)	57.16%	706	8.8%	35%
40.0%	9168	1236	13.48% (±0.36%)	61.20%	1261	13.75% (±0.36%)	62.45%	807	8.8%	40%
45.0%	10314	1336	12.96% (±0.33%)	66.18%	1357	13.16% (±0.33%)	67.22%	908	8.8%	45%
50.0%	11460	1420	12.39% (±0.31%)	70.33%	1424	12.43% (±0.31%)	70.54%	1008	8.8%	50%

* Estimates of the number of readmissions captured by chance in a given cohort size were calculated based on the 8.8% readmission rate in the entire study sample that occurred within 30 days of admissions occurring from June 2008 to May 2009.

CI, Confidence Interval

X% highest risk for readmission (where X is the cohort size) and the percent of 30-day readmissions that were identified within each cohort is shown. These capture rate were then compared to the capture rate that would be expected via random selection from an equally-sized cohort. The models' capture rates were nearly identical, regardless of cohort size. Across cohorts, both models exhibit good discriminative power, correctly predicting actual 30-day readmissions as much as two times more often than chance.

When considering a 25% cohort of the study population's hospitalizations selected via a risk index (i.e. highest risk 25%), the hcRRI model capture rate showed a 2.34% relative improvement over the cRRI model. Furthermore, the hcRRI tool had slightly higher discrimination for 30-day readmissions; the ROC c-statistic in the training was 0.680, and 0.665 in the validation for the hcRRI and 0.662 and 0.658, respectively, for the cRRI.

Comparison of Model Predictive Ability to Selection by Diagnosis

Since individuals with certain diseases are known to have higher readmission rates than the population as a whole, we next compared the readmission rates within hospitalizations primarily related to heart failure, pneumonia and chronic obstructive pulmonary disease (COPD), shown in this population to be the diagnoses most often associated with readmissions, to the readmission rates measured in a model-ranked cohort of the same size (Table 3). For example, among all hospitalizations in the study population, 911 of them were primarily related to heart failure, pneumonia or COPD Among these 911 hospitalizations, 113 resulted in a 30-day readmission. For comparison, a cohort of equal size was selected using the hcRRI model, representing the highest risk 911 admissions among the entire study group irrespective of disease. Of these 911 admissions, 231 cases were readmitted within 30 days, indicating the distinct advantage of this model for proactively identifying individuals who will be readmitted compared with diagnosis-based selection.

TABLE 4: READMISSION RATES IN THE ENTIRE STUDY GROUP BY DIAGNOSIS COMPARED TO READMISSION RATES AMONG A COHORT OF EQUIVALENT SIZE RANKED AS HIGHEST RISK FOR READMISSION, IRRESPECTIVE OF DISEASE, BY TWO RRI MODELS.

Disease	Number of admissions	Readmissions, N (rate)	cRRI, readmissions in equal cohort size, N (rate)	hcRRI, readmissions in equal cohort size, N (rate)
Heart Failure	228	38 (16.7%)	46 (20.1%)	82 (36.0%)
Pneumonia	510	50 (9.8%)	105 (20.6%)	147 (28.8%)
COPD	173	25 (14.5%)	31 (17.9%)	64 (37.0%)
Total	**911**	**113 (12.4%)**	**183 (20.1%)**	**231 (25.4%)**

COPD, chronic obstructive pulmonary disease

DISCUSSION

Our evaluation of readmissions from among nearly 23,000 admissions confirms previous reports that readmissions are a significant problem and that the greatest opportunity to reduce admissions occurs during the time of admission or shortly thereafter since the majority of readmissions occur within 30-days of discharge.[1, 4] The predictive models evaluated here represent effective and flexible tools to identify admitted individuals at highest risk of 30-day readmission. The consistent performance of both predictive models with training and validation data suggests that both RRI models are discriminative and accurate compared with chance and disease-based selection in predicting readmissions that occur in a 30-day timeframe—an important quality indicator and metric that will soon tie directly to reimbursement.[5, 6] Either approach to predicting readmissions offers an empirical method by which hospitals and health plans can target and reduce readmissions—demonstrably better than by selecting individuals based on diagnosis alone. The use of model-derived risk scores to select a subset of admitted patients proved to enrich the sample substantially with individuals who actually were admitted. Although all admitted patients should be provided with quality discharge planning, these tools allow for the highest risk patients to be prioritized for higher-touch discharge support to allow such individualized readmission avoidance programs to remain cost effective as additional support over and above the standard protocol.

Both readmission-risk predictive models described here can be applied during hospitalization and can identify patients who should be prioritized for more intensive discharge planning and follow up with similar accuracy. Therefore, the models provide two options for settings with different data availability. In settings in which historical claims data are readily available, it would be preferable to use the hcRRI model, which performs slightly better than the cRRI that uses only current data if the logistics of using the additional data do not present a barrier. Because obtaining the patient's medical history from the claims pool takes time and is resource intensive, both of which tend to be limited in a clinical setting, the cRRI model offers an alternative means of accurately predicting the risk of readmission. No claims data are necessary. To obtain an RRI, a clinician only needs to know the patient's primary and secondary diagnoses, intensive-care unit usage and a few other key facts easily gleaned from the chart. Together, the models provide options to consider with respect to the trade off in accuracy for the advantages in some settings of using a more manageable or accessible data set. In either case, these models provide a unique opportunity to enhance discharge support in an efficient manner with applicability to various providers of that support.

Although this study demonstrated that historical claims are not absolutely necessary to achieve reasonable predictive ability, this phenomenon may be specific to predicting readmissions, which are defined by their proximity in time to a prior admission and are thus more likely to be associated with data from the timeframe of that admission. The historical data may be critical to models developed to predict other outcomes or that have a more general target, such as predicting future avoidable high-cost medical events.[10] In this case, the models' strength and uniqueness lie in their ability to perform reliably with both historical medical information and information from the current hospitalization, or from current data alone. Using the best of data available, they allow a care provider to capture more opportunity to prevent readmissions within 30 days of discharge by directing higher intensity care toward patients with the highest likelihood of readmission.

Although other researchers have created models to predict readmissions, these have typically had the greatest success in specific population subsets that are either more homogeneous (i.e., a particular hospital or region) and that often have high rates of readmission, such as a senior population.[9] For example, the 30-day readmission rate of our study population (8.8%) is half of the rate reported in Medicare populations (19.6%).[4] While rare events are generally more difficult to predict, the design of this model can predict readmissions even in a population in which they are relatively rare compared to a higher-risk Medicare population. The fact that the model is not limited to a population subset also expands its applicability and thus usefulness. Future work should evaluate the performance of these approaches to modeling readmissions in additional data sets to ensure similar performance in different populations or larger geographic areas.

Even with an accurate model, little can be done to reduce readmissions without effective means of supporting at-risk patients before, during and after the time of discharge from the hospital. As a result of policy initiatives to improve healthcare quality as well as the economic need to reduce unnecessary healthcare costs, various private and government organizations have developed and tested programs to reduce readmissions. For example, the Care Transitions Intervention, developed by Coleman and colleagues, is a 4-week program in which patients and family caregivers work with a coach to learn self-management skills and are provided specific tools to ensure needs are met in their transition from hospital to home.[11, 12] As an alternative or complementary approach, telephonic support for individuals in their homes after discharge has proven to be an effective means of reducing readmissions.[13] Remote follow-up support, such as this post-discharge program, is likely to be even more successful when preceded by, and integrated with, effective pre-discharge planning.

In conclusion, the readmission-risk predictive models presented here represent tools that can be integrated with proven approaches to reduce readmissions to allow these programs to be both scalable and cost effective by directing efforts reliably toward those at highest risk. They overcome many limitations of previous assessment tools; specifically, they can be used with any inpatient population in any setting. The models use as factors the treatment delivered during the admission with or without historical medical information and the surprisingly similar performance of the two, given that other types of models do require historical claims, demonstrates that the choice between RRI models should be decided primarily based on data availability. The hcRRI and cRRI models apply to hospital admission and readmission for any reason—not only emergency admissions, or readmissions stemming from the cause of the index hospitalization. These models proved valid tools to predict readmissions despite the formidable challenge of achieving this goal in a diverse and relatively low-risk population and thus may represent an important contribution to efforts to improve quality and reduce cost associated with unnecessary readmissions.

KEY FINDINGS

The Readmission Risk Indexes tested here:

- Provide the opportunity to increase efficiency of intensive discharge support. For example, the hcRRI provides the opportunity to impact up to 52% of readmissions by delivering a program to only 30% of admitted patients
- Can be used while a patient is hospitalized for early intervention
- Provide flexibility to allow application in settings with varying data availability; i.e. inpatient settings with or without claims
- Can be used with broad patient populations—not only the elderly or those with chronic conditions
- Provides a decided advantage above prioritizing intensive discharge support based on disease/diagnosis alone.

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