Assessment of a novel tool for identifying hospitalized heart failure patients at risk for 30-day readmission, longer length of stay and high cost

Banoff, KM[1,3], Milner, K[2,] Rimar J[3], Greer, AE[3], Canavan, ME[4]

[1]KMB Consulting, LLC; [2]Yale New Haven Health System, New Haven, CT; [3]Sacred Heart University, Fairfield, CT, [4]Yale University School of Public Health, New Haven, CT

Karen Merl Banoff, DNP, RN is the Principal of KMB Consulting, LLC and Adjunct Faculty of Nursing at Sacred Heart University

Kerry Milner, DNSc, RN is an Assistant Professor of Nursing at Sacred Heart University

Joan Rimar, DNSc, RN is a Clinical Management Consultant in the Department of Analytics Strategy & Financial Planning at Yale New Haven Health System.

Anna E. Greer, PhD, CHES, HFS is an Assistant Professor of Exercise Science at Sacred Heart University

Maureen Canavan, PhD is an Associate Research Scientist in the Department of Health Policy and Management at the Yale University School of Public Health

For Correspondence:
Karen Merl Banoff, DNP, RN
KMB Consulting, LLC
91 Old Hollow Road
Trumbull, CT 06611
(203) 209-0681 (day/evening phone)
(203) 459-1601 (fax)

Abstract

PeraTrend's™ Rothman Index (RI) is a new practical tool for prospectively identifying patients at risk for 30-day readmission, extended hospitalization, and high cost. This is the first study measuring the association between the RI and these outcomes in HF patients.

Assessment of a novel tool for identifying hospitalized heart failure patients at risk for 30-day readmission, longer length of stay and high cost

Heart failure (HF) affects 5.1 million Americans with an incidence rate of 10 per 1,000 in people over the age of 64 years (Go, et al., 2013). Annually HF is the underlying cause in more than 56,000 deaths and it is the principal diagnosis in nearly 1 million hospitalizations. Moreover, 30-day readmission rates for this population range from 22 to 25% (Chen, Dharmarajan, Wang, & Krumholz, 2013; Ross et al., 2010). The estimated costs of these 30-day readmissions in Medicare beneficiaries are in excess of 1 billion dollars each year (Hines, Barrett, Jiang & Steiner, 2014). With the advent of pay for performance, the Centers for Medicare & Medicaid Services (CMS) (2012) are imposing financial penalties on hospitals for high 30-day readmission rates for specific diagnoses, including HF. These data underscore the need to identify and evaluate practical tools that assist clinicians with real-time decision making when caring for all types of patient populations at high risk for readmission.

PeraTrend™ is a new patient acuity software that continuously extracts clinical data from the electronic medical record (EMR) to calculate a validated Rothman Index (RI) which is a measure of the patient's current condition (Rothman, Rothman, & Beals, 2013; Rothman, Solinger, Rothman & Finlay,). This index can be used by clinicians to make decisions about which patients are ready to be transferred from a critical care unit to a floor or discharged to home or an extended care facility. Readiness for discharge is one of the major factors affecting readmission rates (Stone & Hoffman, 2010).

A large New England healthcare system adopted PeraTrend™, in part, as a potential tool to identify patients at increased risk for unplanned readmission. This healthcare system was selected as the study site to determine if the RI can prospectively identify HF patients at risk for 30-day readmission, extended hospitalization, and high inpatient cost of care.

Readmission rates and costs. When clinicians fail to accurately assess a patient's readiness for discharge, the wrong decision can result in either a longer than necessary hospitalization that may be inadequately reimbursed, or a hospital readmission because of premature discharge (Stone & Hoffman, 2010). Readmission occurs in approximately 18% of all Medicare patients' hospitalizations and the financial impact is significant. The Medicare Payment Advisory Commission (MedPAC) identified that potentially avoidable or preventable readmissions cost Medicare approximately $12 billion annually (Hackbarth, 2009).

Centers for Medicaid and Medicare Services implemented its hospital readmission reduction program, a part of the Patient Protection and Affordable Care Act (PPACA), which requires CMS to reduce payments to hospitals with excessive readmissions. The program applies to discharges from October 1, 2012 forward and includes readmission for any reason within 30 days of discharge for three groups of patients; HF, pneumonia and myocardial infarction (Centers for Medicare & Medicaid Services, 2012). Readmission for HF patients is a significant problem. Between 2004 and 2006, the readmission rate for any reason within 30 days was 23.8% for Medicare beneficiaries discharged from the hospital with a HF diagnosis (Ross et al., 2010).

Tools to predict 30-day readmission. Prediction of readmission in the clinical setting has proven to be difficult and complex, particularly for HF patients. There are few clinically relevant tools/models to predict 30-day readmission and hospital length of stay (LOS) for HF patients (Amarasingham et al., 2010; Muzzarelli, et al., 2010; Whellan et al., 2011). Most of the existing tools/models rely on administrative data that are not available until after discharge, precluding their use for real-time clinical decision making (de Lissovoy, 2013). A systematic review of statistical models to predict a HF patients' risk of readmission conducted by Ross et al., (2008) revealed substantial inconsistencies in patient characteristics that were predictive of readmission in this population. Kansagara et al. (2011) conducted a systematic review of risk prediction models for hospital readmission not specific to HF. Twenty-six models were reviewed with a few applicable in the clinical setting. Most models relied on retrospective administrative data, however a few relied on real-time administrative data. Some of the models incorporated primary data collection. Most models had C-statistics in the range of 0.6 – 0.7 and the authors concluded the overall predictive ability of the models was fair.

Literature regarding readmission prediction tools in use in the clinical setting was sparse. Van Walraven et al. (2010) developed the LACE index which relies on four variables; LOS ("L"), acuity of the admission (e.g. emergency admission) ("A"), Charlson Comorbidity index score ("C") and the number of previous emergency department visits in the past 6 months ("E"). The LACE index was validated using a mix of medical and surgical patients. Wang, et al. (2014) tested the LACE index with HF patients and found that the index did not reliably predict unplanned readmission within 30 days. Similarly, in a study of general medical patients in the United Kingdom the LACE index was found to have fair predictive value for 30-day readmission with a C-statistic of .55 (Cotter, Bhalla, Wallis & Biram, 2012) and in medical patients in Canada, the index identified only half the patients readmitted within 30 days of discharge (Grunier et al., 2011).

Choudhry et al. (2013) developed all-cause hospital readmission risk prediction models to identify adult patients at high risk for 30-day readmission upon admission and discharge. Both models showed moderate discrimination ability with a C-statistic of 0.76 and 0.78, respectively. These researchers collaborated with Cerner, an EMR vendor, to develop an automated algorithm within the EMR which transitioned the model to a usable tool in the clinical setting called the HOSPITAL score. The HOSPITAL score includes 7 variables; hemoglobin at discharge, discharge from oncology, sodium level at discharge, having a procedure, type of admission, number of admissions in past year and LOS. The HOSPITAL score was shown to have fair discriminatory power (C-statistic of 0.71) for prediction of 30-day readmission in medical patients (Donze, Aujesky, Williams & Schnipper, 2013).

Neither the LACE index nor the HOSPITAL score includes information from nursing assessments in their estimation of risk for 30-day readmission. They also lack data on the patient's condition throughout the hospitalization. In order to address the problem of 30-day readmissions clinicians need an easy to use risk prediction tool that works in real-time, using continuous patient specific clinical data, and is independent of the patient's diagnosis.

The RI by PeraTrend™. The RI is calculated by using real-time data from the patient's EMR at multiple times during the hospital day (Bradley et al., 2013; Rothman, Rothman, & Beals, 2013). The RI has been clinically validated using diverse patient populations in several hospitals. The RI is calculated from 26 clinical measures including vital signs (temperature, blood pressure, pulse oximetry, respiratory rate, and heart rate), nursing assessments (cardiac, respiratory, gastrointestinal, genitourinary, neurological, skin, safety, peripheral vascular, food/nutrition, psychosocial, and musculoskeletal), Braden score, laboratory blood tests (creatinine, sodium, chloride, potassium, BUN, WBC, and hemoglobin), and cardiac rhythm. An unimpaired patient has an RI of 100; the score drops as condition deteriorates. Clinically meaningful RI scores can range from -40 to 100.

Inclusion of nursing assessment data in the RI score is unique and has not been done in previous acuity or readmission prediction tools or scores. These nursing assessment data contribute to 47% of the RI and the developers found these assessments were strongly correlated with in-hospital and post discharge mortality (Rothman, Rothman & Beals, 2013). Moreover the developers hypothesized that the nursing assessments strengthen the ability of the RI to be used by clinicians to identify subtle patient deterioration prior to vital sign changes (Rothman, Solinger, Rothman & Finlay, 2012).

Figure 1 shows one patient's RI graph as it appears in the EMR. The RI score is plotted on the y-axis and the day of the hospitalization on the x-axis. The higher the RI, the less physiologically impaired the patient. The RI itself reflects the risk of a patient dying or being transferred to hospice within 48 hours and the risk grows as the score decreases. The red and yellow lines represent the dividers between the three RI zones. The red zone, which is below the red line, includes RI scores <40 and represents the sickest patients. Scores between 40 and 65 are between the red and yellow lines, and represent the yellow zone. This zone is meant to cue the clinician to closely monitor the patient. Scores between 65 and 100 are above the yellow line and represent the blue zone. Patients in this zone are the most clinically stable. The RI graph in Figure 1 illustrates a patient admitted to the hospital on a Monday with an RI score just above 20 and therefore in the red zone. Throughout the two week hospitalization the score increased and except for a few instances, remained in the yellow zone. Although it is ideal for patients to reach the blue zone prior to discharge, this may not be achievable when there are a number of chronic conditions.

Figure 2 demonstrates a four patient view over a 5-day timeframe. Clinicians can view RI graphs for an individual patient or for a group of patients (e.g., a nursing unit, a customized patient list) by any number of hospital days or for full hospitalizations. Multi-patient views are helpful to clinicians who are responsible for a group of patients and can be used to quickly assess individual patient conditions in order to prioritize patient care activities and discharges. Figure 2 includes one patient in the red zone, one in the yellow zone and two in the blue zone. The patients in the red and yellow zones should be prioritized for nursing observation and intervention.

There are few published studies using the RI. Bradley, Yakusheva, Horwitz, Sipsma and Fletcher (2013) conducted a retrospective analysis to measure the association between the RI at discharge and unplanned 30-day readmission in medical and surgical patients. They identified four categories of RIs and found that the odds of unplanned 30-day readmission were significantly higher in higher risk (e.g. lower RI score) groups compared with patients in the lowest risk group. Tepas, Rimar, Hsiao and Nussbaum (2013) found the RI trend useful in identifying patients with post-operative complications following colorectal procedures. Piper et al. (2014) investigated the usefulness of the RI at time of transfer out of the surgical intensive care unit (SICU) in predicting early SICU readmission. These researchers found a correlation between higher RI (greater than 82.9) and appropriate transfer from the SICU to the floor and SICU readmission within 48 hours correlated with a decreased RI.

Tools for predicting LOS. There are a few tools that have been shown to predict LOS in hospitalized patients (Kasotakis, G., et al., 2012; Tan, et al., 2014; Wagener, G. et al., 2011). The major limitation of these tools is that they predict LOS in surgical patients only. A review of the literature did not uncover any tools for predicting LOS in patients with medical conditions or HF.

In summary, existing tools/models for predicting 30-day readmission and LOS have limitations. Therefore, the authors sought to determine if the newly developed RI can prospectively identify HF patients at risk for 30-day readmission. The authors hypothesized that poor patient condition (low RI) prior to discharge would increase risk for 30-day readmission and poor patient condition (low RI) upon admission would be associated with increased LOS and healthcare costs.

Methods

Research Design and Setting

A retrospective design using purposive sampling over a time-limited period was used to determine if the RI prospectively identified HF patients at risk for 30-day readmission, extended hospitalization, and high inpatient cost of care in a large New England healthcare system. This healthcare system has a data warehouse that stores data from multiple hospital databases, including, but not limited to, registration, billing, EMR and cost accounting systems. Data for this study were easily extracted from this system.

Sample

This study was approved by the Institutional Review Board of the School of Medicine associated with the healthcare system. Purposive sampling was used to select all adult HF patients (age ≥ 18 years), discharged from the study hospital during the 12 months between October 1, 2011 and September 30, 2012 who had a principal diagnosis of HF as defined by one of the ICD-9-CM codes in Table 2. All patients were included unless they died in the hospital (n=32) or were discharged to a hospice facility or home hospice (n=26). These exclusion criteria were selected because patients who died while hospitalized or who were expected to die soon after discharge could skew the dependent variables. One additional patient was excluded due to missing data. A total of 985 patients were included in the analyses.

Major Variables

Dependent variables. Three distinct outcomes were measured. Thirty-day readmission was defined as patient re-hospitalization within 30 days following discharge after an initial hospitalization for HF. The LOS was measured as the difference, in days, between the date of admission and the date of discharge. Healthcare cost was defined as direct variable costs (DVC) of care and included the cost of products and services provided directly to patients such as pharmaceuticals, radiologic and laboratory tests, medical-surgical supplies, and room and board.

Main independent variable. The RI was the main independent variable. To analyze 30-day readmission, the patients' last RI before discharge was used. In a previous study, the last RI score was helpful in predicting patients at highest risk of readmission (Bradley et al., 2013). To analyze LOS and DVC the first RI upon hospital admission was used because the clinicians use this RI to identify patients at risk for poor outcomes.

Covariates included gender, race, marital status, age, and whether the diagnosis-related group (DRG) assigned was medical or surgical. Gender was defined as male or female; marital status as currently married, formerly married or single. Age was defined in years by subtracting the admission date from the date of birth. Race was defined as white, black and other and DRG type was defined as medical or surgical, as assigned by CMS. In order to determine the independent association between RI and readmission, these covariates that have been hypothesized to be associated with readmission in other studies, were collected for inclusion in the multivariate analyses (Ross et al., 2008; Chen et al., 2013; and Piper et al. 2014). Medical and surgical DRG type was included to distinguish between patients who experienced a major surgical or invasive procedure during their hospitalization from those who did not. The authors hypothesized that discharge disposition could affect the need for re-hospitalization and therefore it was included to differentiate between patients who received post hospital discharge care such as home health or skilled nursing facility care and those who did not.

Data Analysis

Prior to conducting data analyses, standard data cleaning procedures were applied to screen for errors, potential outliers, and violations of statistical assumptions. For readmission analyses, the data were separated into 4 quartiles across the range of RI values at discharge in order to facilitate the identification of clinically meaningful and statistical relationships with 30-day readmission. The RIs were placed into the following risk quartiles: high risk (RI < 60), medium risk (RI = 60-72), low risk (RI = >72-80), and lowest risk (RI > 80). An increase or decrease of a few points in the RI was unlikely to impact 30-day readmission and a range of RIs, which indicates a risk level, produced more differentiation (Bradley et al., 2013). The quartiles were tested against a larger sample of patients tested and validated by Bradley et al., (2013) and there were no significant differences found from the quartiles identified in this study; therefore the risk quartiles as described were utilized.

Logistic regression was used to determine the predictive value of the last RI on 30-day readmission. Multiple regression was used to predict the effect of the first RI on LOS and DVC. All multivariate models included the RI and the covariates of gender, race, marital status, age and DRG type. The Variance Inflation Factor (VIF) and multicolinearity were assessed for each model and the result indicated that no predictors needed to be removed from the models. A C-statistic was calculated for each of the last RI risk quartile cut-points to measure the ability of the last RI categories to discriminate between discharges that were followed by a readmission within 30 days of discharge and those that were not. All analyses were conducted using SAS 9.3(SAS Institute, Inc., Carey, NC).

Results

A total of 985 patients with HF were analyzed for this study and their descriptive statistics appear in Table 2. The mean age of these patients was 71 years with slightly more males. The sample was mostly white, not married patients with a medical DRG. Most patients were discharged to home with home health care. The overall sample mean admission RI was 67.4 and the mean discharge RI was 69.9. In readmitted patients the mean admission and discharge RIs were significantly ($p<.001$) lower indicating poorer patient condition compared to patients who were not readmitted.

A total of 267 (27%) patients were readmitted to the study hospital within 30 days. The overall mean LOS and DVC for the entire sample was 7.2 days and $11,312 respectively. The LOS and DVC were significantly ($p<.027$) higher in readmitted patients versus non-readmitted patients.

Table 3 summarizes the logistic regression models for the last RI (categories) and 30-day readmissions while controlling for age, race, marital status, sex, and DRG type. The likelihood of readmission to the hospital within 30 days was 2.6 times higher in patients in the high risk category (RI<60); 2.4 times higher in patients in the medium risk category (RI= 60 to 72) and 2.3 times higher for patients in the low risk category (RI== >72-80) compared with patients in the lowest risk category (RI>80). The C-statistic (0.614) and ROC curve illustrate (see Figure 3) that the last RI score had fair ability to detect individuals at risk for readmission.

Table 4 summarizes the results for the multiple regression model using first RI to predict LOS. In this model a higher first RI (better patient condition) was significantly (p<.001) associated with a shorter LOS by 0.12 days. Table 5 summarizes the multiple regression model using first RI to predict DVC and a higher first RI was significantly (p<.001) associated with lower DVC by $194.95.

Discussion

Using a large sample of hospitalized patients with HF the authors found that the RI, which is a measure of the patient’s condition that uses clinical data from the EMR, was significantly associated with 30-day readmission. Similarly, Bradley et al. (2013) reported that adult medical surgical patients with a RI<70 were 2.65 times more likely to be readmitted within 30 days. The 30-day readmission rate for the current study was 27% which was slightly higher than the rates from 22 to 25% reported in other studies (Chen, Dharmarajan, Wang, & Krumholz, 2013; Ross et al., 2010).

This study demonstrated that the initial RI was also a significant independent predictor of LOS and DVC in hospitalized HF patients and supported the authors' hypothesis that lower RIs upon admission predicted longer LOS and increased DVC. Similarly, in patients undergoing laparoscopic surgery, Tepas and colleagues (2013) reported a significant ($p<.001$) negative correlation between initial RI and LOS and DVC, as patient condition worsened (lower RI), LOS and DVC increased.

Although there are other readmission and LOS prediction tools (e.g. LACE Index, HOSPITAL score), none use real-time, continuous patient data. Moreover these tools lack nursing assessment data which, when coupled with vital signs are more sensitive to subtle changes in patient condition than vital signs alone. Many times the patient condition in the HF population can change rapidly so real-time RIs allow clinicians to make decisions tailored to patient risk up to the point of discharge.

Limitations

The findings of this study need to be viewed in light of several limitations. This study was conducted at a single hospital and the HF population and clinician practices may be different at other institutions. Future studies should include multiple sites in order to account for patient and practice variations. There was no way to identify readmissions to other hospitals and it is possible that some HF patients sought care elsewhere. Bradley and colleagues (2013) estimated a 15% readmission rate to other hospitals using CMS data and hypothesized that this omission could affect the C-statistic but the direction cannot be predicted. All data were requested for a 12-month period and yielded 985 patients. Although this sample size was sufficient for the analyses done, it is possible that the power to detect significant interaction effects was lacking.

Lastly there was no adjustment for socioeconomic factors that can impact readmission and LOS because the administrative data system did not include data on education level, family support, and access to post-acute care primary care (Amarasingham et al., 2010; Bradley et al., 2013).

Conclusion

This study confirmed a statistically significant independent association between the RI (at discharge) and 30-day readmission, the RI (upon admission) and LOS, and the RI (upon admission) and DVC. PeraTrend™ patient acuity software can be readily installed in the EMR to extract continuous patient data on clinical data elements, including nursing assessments, to calculate a RI. This real-time patient condition index can be used by clinicians to make decisions about which patients are ready to be transferred from a critical care unit to a floor or discharged. The RI can also be used to predict which patients are at highest risk for 30-day readmission and interventions can be initiated to prevent an unplanned readmission. Clinical decision making using real-time patient condition indices like the RI may also decrease LOS and healthcare costs.

Figure 1. A Patient's Rothman Index Graph (full hospitalization)

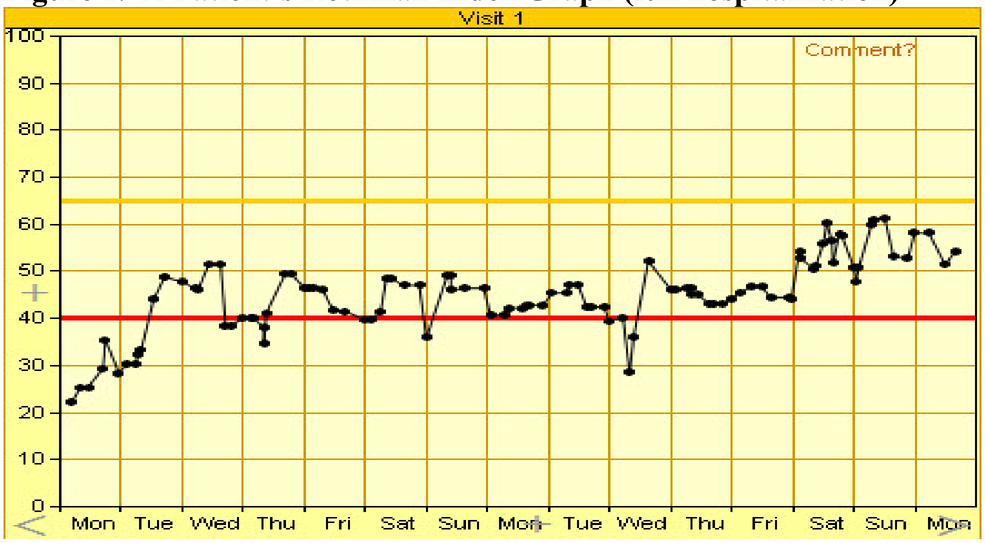

Figure 2. Rothman Index Graphs for 4 Patients for a 5-Day Period.

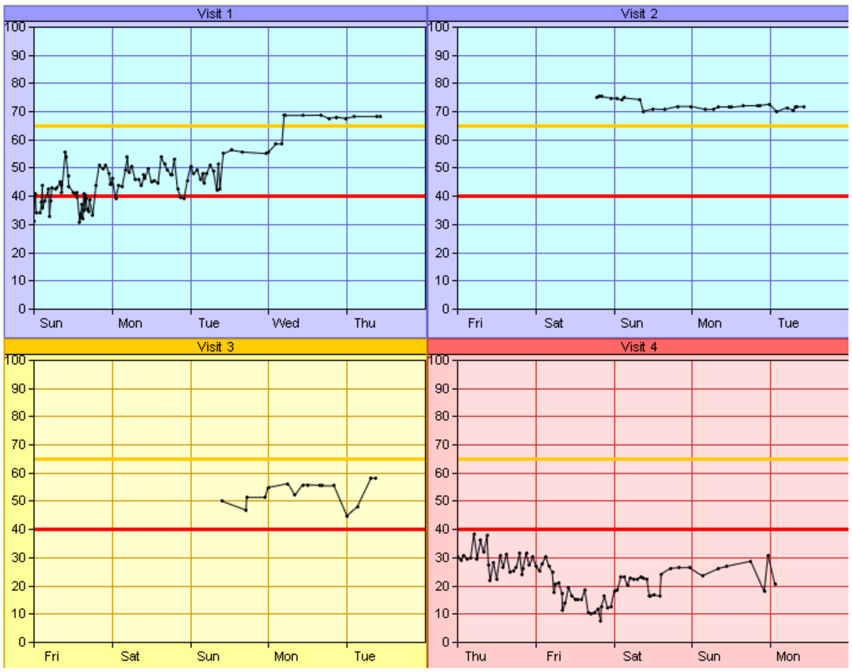

Figure 3: Overall Model ROC curve using Last RI scores as a predictor of 30-day readmission

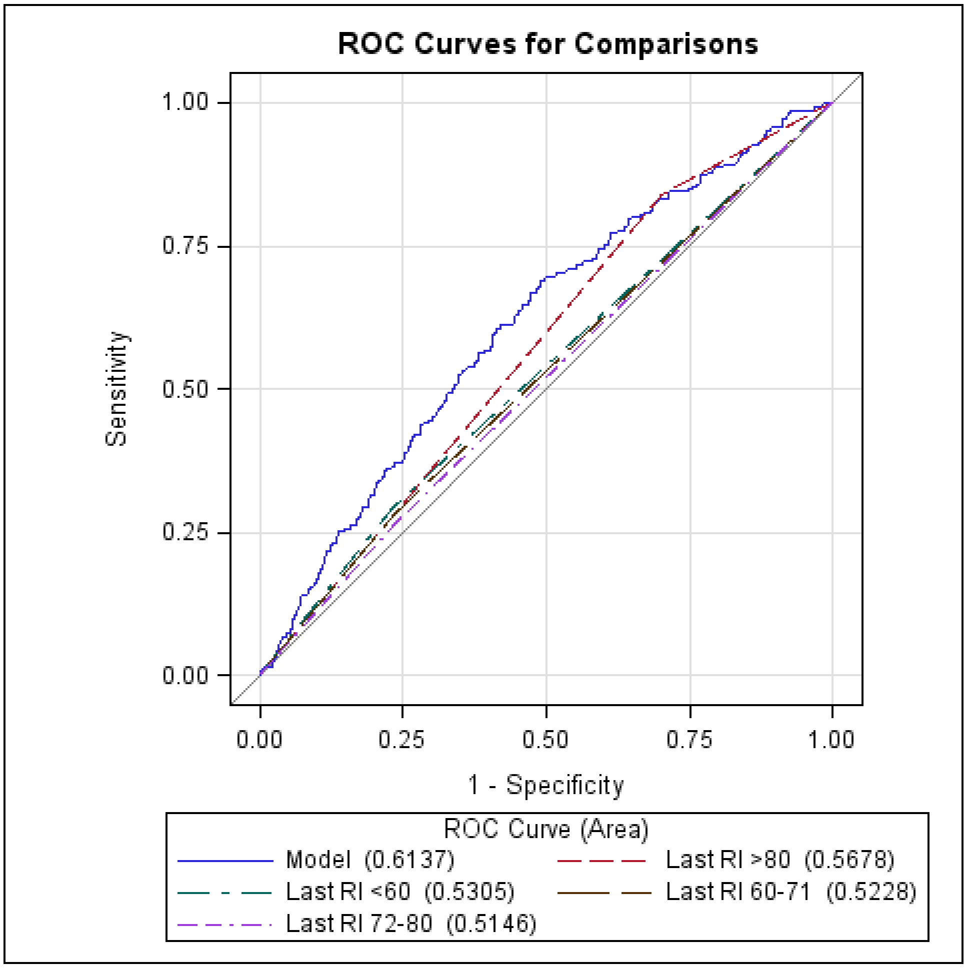

Table 1: Center for Medicare and Medicaid Services' ICD-9-CM Codes for Heart Failure

ICD 9 Code	Description
402.01	Hypertensive heart disease, malignant, with heart failure
402.11	Hypertensive heart disease, benign, with heart failure
402.91	Hypertensive heart disease, unspecified, with heart failure
404.01	Hypertensive heart and chronic kidney disease, malignant, with heart failure and with chronic kidney disease stage I through state IV, or unspecified
404.03	Hypertensive heart and chronic kidney disease, benign, with heart failure and with chronic kidney disease stage I through state IV, or unspecified
404.11	Benign hypertensive heart and renal disease with CHF
404.13	Hypertensive heart and chronic kidney disease, benign, with heart failure and chronic kidney disease stage V or end stage renal disease
404.91	Hypertensive heart and chronic kidney disease, unspecified, with heart failure and with chronic kidney disease stage I through stage IV, or unspecified
404.93	Hypertensive heart and chronic kidney disease, unspecified, with heart failure and chronic kidney disease stage V or end stage renal disease
428.xx	Heart failure:
428.0	Congestive heart failure, unspecified
428.1	Left heart failure
428.20-23	Systolic heart failure
428.30-33	Diastolic heart failure
428.40-43	Systolic & diastolic heart failure

Note. Adapted from "Hospital 30-Day Heart Failure Readmission Measure Methodology," by H. Krumholz, S. L. Normand, P. Keenan, Z. Lin, E. Dryer, K. Bhat, . . . G. Schreiner, 2008, p.6. Copyright © 2008 by the Centers for Medicare & Medicaid Services (CMS).

Table 2. Sample Characteristics (N=985)

Variable	Overall sample N=985	Patients not readmitted n=718	Patients readmitted n=267	P-value*
	Mean (SD)	Mean (SD)	Mean (SD)	
Length of stay	7.2 (8.1)	6.8 (7.2)	8.3 (9.9)	0.027
Direct variable cost ($)	11,312.50 (24,408.29)	9,644.13 (15,529.98)	15,798.97 (39,064.88)	0.013
First RI	67.4 (18.1)	68.6 (17.8)	64.2 (18.6)	<0.001
Last RI	69.9 (15.8)	71.2 (15.6)	66.6 (15.7)	<0.001
Low RI	53.3 (22.1)	54.9 (22.1)	49.2 (21.5)	<0.001
Age	71.4 (15.3)	71.5 (15.5)	71.3 (14.9)	0.827
	N (column %)	N (column %)	N (column %)	
Sex				0.052
Male	548 (55.6)	386 (53.8)	162 (60.7)	
Female	437 (44.4)	332 (46.2)	105 (39.3)	
Race				0.586
White	656 (66.6)	478 (66.6)	178 (66.7)	
Black	226 (22.9)	161 (22.4)	65 (24.3)	
Other	103 (10.5)	79 (11.0)	24 (9.0)	
Marital Status				0.878
Married	395 (40.1)	290 (40.4)	105 (39.3)	
Single	197 (20.0)	145 (20.2)	52 (19.5)	
Formerly married	393 (39.9)	283 (39.4)	110 (41.2)	
Discharged location				<0.001
Home	297 (30.2)	242 (33.7)	55 (20.6)	
Skilled nursing facility	240 (24.4)	162 (22.6)	78 (29.2)	
With home health aid	410 (41.6)	291 (40.5)	119 (44.6)	
Other	38 (3.9)	23 (3.2)	15 (5.6)	
DRG type				0.644
Medical	859 (87.2)	94 (13.1)	32 (12.0)	
Surgical	126 (12.8)	624 (86.9)	235 (88.0)	

Table 3: Logistic regression models examining the predictive value of the last RI on 30-day readmission (N=985)

		95% CI	
	OR	LL	UL
Last RI score[a]			
High Risk (RI<60)	2.63	1.68	4.11
Medium Risk (RI 60-71)	2.40	1.54	2.30
Low Risk (RI 72-80)	2.30	1.47	3.59
Female	0.69	0.72	1.57
Race[b]			
Black	1.06	0.72	1.57
Other Race	0.84	0.51	1.41
Marital Status[c]			
Single	0.95	0.62	1.47
Formerly Married	1.14	0.80	1.60
Age	0.99	0.98	1.00
DRG Type[d]			
Medical	1.00	0.64	1.57

Note. CI = confidence interval; OR = odds ratio; UL = upper limit; LL = lower limit. [a]The reference category is lowest risk RI>80. [b]White. [c]Current partnered. [d]Surgical DRG. Last RI High Risk ($p<0.001$), Medium Risk ($p<0.001$), Low Risk ($p<0.001$), Female ($p=0.019$).

Table 4
Multiple Regression Model Predicting Effect of First RI and LOS

Variable	Model *B*	95% CI
First Rothman Index Score	-0.12**	[-0.14, -0.10]
Female	0.23	[-1.19, 0.73]
Race		
White	Reference	
Black	0.20	[-1.43, 1.03]
Other race	0.77	[-2.32, 0.78
Marital Status		
Currently married	Reference	
Single	1.54*	[0.19, 2.89]
Formerly married	0.91	[-0.19, 2.01]
Age	0.08**	[-0.12, -0.04]
DRG Type		
Medical	8.52**	[-9.91, -7.13]
Surgical	Reference	
R^2	0.2032	
F	31.1**	

Note. N=985. *p < .05, **p < .001.

Table 5
Multiple Regression Model Predicting Effect of First RI on DVC

Variable	Model *B*	95% CI
First Rothman Index Score	-194.95**	[-265.42, -124.49]
Female	2,269.50	[-4,895.39, 356.39]
Race		
White	Reference	
Black	2,866.15	[-6,261.38, 529.08]
Other race	3,141.08	[-7,377.11, 1,094.95]
Marital Status		
Currently married	Reference	
Single	1,813.20	[-1,886.50, 5,512.90]
Formerly married	2,828.01	[-175.79, 5,831.81]
Age	296.70**	[-399.29, -194.11]
DRG Type		
Medical	40,087.00**	[-43,879.69, -36,276.31]
Surgical	Reference	
R^2	0.3506	
F	65.9**	

Note. N=985. **p* < .05, ***p* < .001.

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