ORIGINAL ARTICLE

Predictive Model for Heart Failure Readmission Using Nationwide Readmissions Database

Lillian Zheng, MD; Nathan J. Smith, MD; Bi Qing Teng, MS; Aniko Szabo, PhD; and David L. Joyce, MD, MBA

Abstract

Objective: To generate a heart failure (HF) readmission prediction model using the Nationwide Readmissions Database to guide management and reduce HF readmissions.

Patients and Methods: A retrospective analysis was performed for patients listed for HF admissions in the Nationwide Readmissions Database from January 1, 2010, to December 31, 2014. A Cox proportional hazards model for sample survey data for the prediction of readmission for all patients with HF was implemented using a derivation cohort (2010-2012). We generated receiver operating characteristic (ROC) curves and estimated area under the ROC curve at each time point (30, 60, 90, and 180 days) to assess the accuracy of our predictive model using the derivation cohort (2010-2012) and compared it with the validation cohort (2013-2014). A risk score was computed for the validation cohort. On the basis of the total risk score, we calculated the probability of readmission at 30, 60, 90, and 180 days.

Results: Approximately 1,420,564 patients were admitted for HF, contributing to 1,817,735 total HF admissions. Of these, 665,867 patients had at least 1 readmission for HF. The 10 most common comorbidities for readmitted patients included hypertension, diabetes mellitus, renal failure, chronic pulmonary disease, deficiency anemia, fluid and electrolyte disorders, obesity, hypothyroidism, peripheral vascular disorders, and depression. The area under the ROC curve for the prediction model was 0.58 in the derivation cohort and 0.59 in the validation cohort.

Conclusion: The prediction model will find clinical utility at point of care in optimizing the management of patients with HF and reducing HF readmissions.

 ■ Mayo Clin Proc Inn Qual Out 2022;6(3):228-238

From the Department of Medicine (L.Z.), Division of Cardiothoracic Surgery, Department of Surgery (N.J.S., D.J.), and Division of Biostatistics, Institute for Health & Equity (B.Q.T., A.S.), Medical College of Wisconsin, Milwaukee.

Heart failure (HF) is a growing public health problem despite advances in diagnosis and management.[1-4] Although there has been a slight improvement in survival after HF, primarily attributed to evidence-based approaches targeting HF risk factors and implementation of HF therapies, the benefits have not been proportional to the efforts invested in HF management.[5,6] With almost 25% of patients with previous HF admissions readmitted in the next 30 days, HF readmissions accounted for $903 million in Medicare in 2008.[7,8]

In 2005, Medicare reported that the 7- and 30-day readmission rates for HF were 6.2% and 17.6%, respectively, most of which were considered preventable. To curtail the formidable Medicare reimbursements, the Hospital Readmissions Reduction Program under the Affordable Care Act was created to penalize hospitals with high rates of readmissions by reducing hospital reimbursements. With the increased incentive to reduce readmission rates, it is important to identify factors associated with higher readmission risk. To that effect, many predictive models have been proposed. A notable example is the predictive model proposed by Chamberlain et al,[9] which used the State Inpatient Database (SID) to develop a prediction model for HF readmissions on the basis of 4 states. Although accurate in its risk-assessment capacity, this model is limited in its generalizability, lacks several important cardiovascular health variables, and has not been validated.

In this study, we examined a large cohort of patients with HF from a national database to determine factors associated with hospital readmission that were used to develop a predictive risk model for HF readmission. This was compared with existing models to validate its risk-assessment capacity. This model may aid in determining interventions to decrease the risk of readmission before discharge by guiding preventative efforts and contributing to measures to reduce health care costs.

PATIENTS AND METHODS

We performed a retrospective review of patients listed for HF admission between January 2010 and December 2014 from the Nationwide Readmissions Database (NRD), which is drawn from the Healthcare Cost and Utilization Project SID and can be used to create estimates of national readmission rates for all patients, regardless of the expected payer for the hospital.[10] Compared with the SID, which is state-based, the NRD is a national database can be used to address a large gap in health care data—the lack of nationally representative information on hospital readmissions for all ages, thus improving generalizability. Additionally, this database includes data on various cardiovascular procedures common among patients with HF, which can impact readmission risk.

We used unique NRD_VisitLinks, which is a variable used to track multiple hospital admissions for the same patient across hospitals within a state within 1 year. All HF-related admissions, including potential multiple admissions of the same patient, were followed until a readmission. Discharges without a readmission within the same year were assumed to have been followed from the middle of the discharge month to December 31 of the corresponding year and censored at that time or at 345 days of follow-up, whichever was earlier. All analyses were adjusted for the survey design, including stratification factors, clustering by hospital ID, and NRD-provided discharge weights. For descriptive analyses, we used weighted Kaplan-Meier analysis to estimate the probability of readmission over time for subsets of admissions defined by the types of HF procedures performed at each admission. An admission that has multiple procedures would contribute to multiple subsets for these estimates. A multivariate Cox proportional hazards model for sample survey data to predict readmission for all patients with HF was implemented using a derivation cohort (2010-2012). All nonsignificant variables at 0.01 level were removed and a multivariate Cox proportional hazards model for sample survey data was refit using the derivation cohort. The score for each variable was calculated as log (hazard ratio) × 10 rounded to the nearest integer. Variables with a small effect size were assigned a score of 0 as a result of this calculation and thus were not included in the final scoring model. This HF readmissions risk scale was then applied to the validation cohort.

Using an inverse probability of censoring weighting approach, we generated time-dependent receiver operating characteristic (ROC) curves and estimated area under the ROC curve (AUC) at each time point (30, 60, 90, and 180 days) to assess the accuracy of our predictive model using the derivation cohort and compared it with the validation cohort (2013-2014).[11] Furthermore, we compared our predictive model to that developed by Chamberlain et al.[9] Because of the small number of admissions in some score groups in the validation cohort, for reporting, some groups were combined such that each group has at least 100 HF admissions. On the basis of the total risk score in the validation cohort, we calculated the probability of readmission at 30, 60, 90, and 180 days using weighted Kaplan-Meier analysis. Analyses were performed using SAS 9.4 (SAS Institute).

RESULTS

Between January 2010 and December 2014, an average of 284,113 patients were admitted for HF each year, contributing 1,817,735 HF admissions for 1,420,564 unique NRD_VisitLinks. A total of 665,867 of the NRD_VisitLinks had at least 1 readmission for HF within the same year (Supplemental Table S1, available online at http://www.mcpiqojournal.org). Table 1 shows the demographic characteristics of all 1,817,735 HF admissions. The probabilities of readmission at 30 days in the derivation and validation cohorts were 0.242 and 0.228, respectively. The patients had a mean age of 72.8 years

TABLE 1. Demographic Characteristics of all 1,817,735 Heart Failure Admissions

Variable	Description	N	Weighted N	All admissions
N				1,817,735
Weighted N				4,266,863
Sex				% (SE)
	Female	890,910	2,107,959	49.4 (0.1)
	Male	926,825	2,158,904	50.6 (0.1)
Age (y) at admission, mean		1,817,735	4,266,863	72.38 (0.089)
Age categories (y) at admission				
	0-39	42,465	101,454	2.38 (0.05)
	40-49	94,971	218,081	5.11 (0.07)
	50-59	221,239	507,828	11.9 (0.11)
	60-69	333,765	778,166	18.2 (0.08)
	70-79	426,452	1,000,804	23.5 (0.08)
	80+	698,843	1,660,530	38.9 (0.22)
Heart failure category				
	Heart failure	464,307	1,073,076	25.1 (0.31)
	Systolic heart failure	653,039	1,525,770	35.8 (0.22)
	Diastolic heart failure	524,579	1,239,760	29.1 (0.18)
	Combined systolic and diastolic heart failure	175,810	428,257	10 (0.12)
Expected primary payer				
	Medicare	1,364,870	3,246,555	76.3 (0.2)
	Medicaid	168,324	364,141	8.55 (0.13)
	Private insurance	183,964	433,401	10.2 (0.11)
	Self-pay	50,857	114,091	2.68 (0.05)
	No charge	5178	11,945	0.28 (0.02)
	Other	40,101	86,718	2.04 (0.05)
Median household income quartiles for patients by ZIP code				
	First	592,230	1,454,270	34.6 (0.43)
	Second	446,097	1,073,297	25.5 (0.26)
	Third	406,498	925,084	22 (0.25)
	Fourth	344,113	750,377	17.9 (0.34)
Length of stay (d), mean		1,817,735	4,266,863	5.032 (0.018)
Length of stay (d)				
	≤2	495,772	1,147,337	26.9 (0.12)
	3	335,132	793,969	18.6 (0.05)
	4	261,430	621,843	14.6 (0.04)
	5	186,217	442,546	10.4 (0.04)
	6	135,249	320,993	7.52 (0.03)
	≥7	403,935	940,175	22 (0.12)
Total charges, mean		1,817,735	4,266,863	37,532 (336.4)
Elective admission		108,805	303,496	7.12 (0.17)
Resident of the state in which hospital care was received		1,757,129	4,098,399	96.1 (0.14)

Mayo Clin Proc Inn Qual Out ■ June 2022;6(3):228-238 ■ https://doi.org/10.1016/j.mayocpiqo.2022.04.002
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TABLE 2. Top 10 Comorbidities of Total Heart Failure Admissions[a]

Variables	Description	N	Weighted N	All admissions
N				1,817,735
Weighted N				4,266,863
All patients refined DRG: risk of mortality subclass[b]				% (SE)
	0: No class specified	44	107	0 (0)
	1: Minor likelihood of dying	208,475	480,434	11.3 (0.09)
	2: Moderate likelihood of dying	761,713	1,803,514	42.3 (0.11)
	3: Major likelihood of dying	662,999	1,555,347	36.5 (0.1)
	4: Extreme likelihood of dying	184,504	427,461	10 (0.07)
All patients refined DRG: severity of illness subclass[c]				
	0: No class specified	44	107	0 (0)
	1: Minor loss of function	141,967	329,041	7.71 (0.06)
	2: Moderate loss of function	699,800	1,656,786	38.8 (0.13)
	3: Major loss of function	827,233	1,937,335	45.4 (0.12)
	4: Extreme loss of function	148,691	343,594	8.05 (0.07)
AHRQ comorbidity measure				
	Deficiency anemia	541,512	1,244,801	29.2 (0.14)
	Chronic pulmonary disease	669,999	1,585,487	37.2 (0.12)
	Depression	165,775	411,698	9.65 (0.08)
	Diabetes, uncomplicated	619,833	1,457,991	34.2 (0.11)
	Diabetes with chronic complications	197,756	446,011	10.5 (0.08)
	Hypertension	1,382,537	3,217,406	75.4 (0.15)
	Hypothyroidism	295,399	699,559	16.4 (0.09)
	Fluid and electrolyte disorders	526,249	1,231,392	28.9 (0.13)
	Obesity	328,886	770,234	18.1 (0.1)
	Peripheral vascular disorders	219,268	504,371	11.8 (0.09)
	Renal failure	744,033	1,729,780	40.5 (0.14)

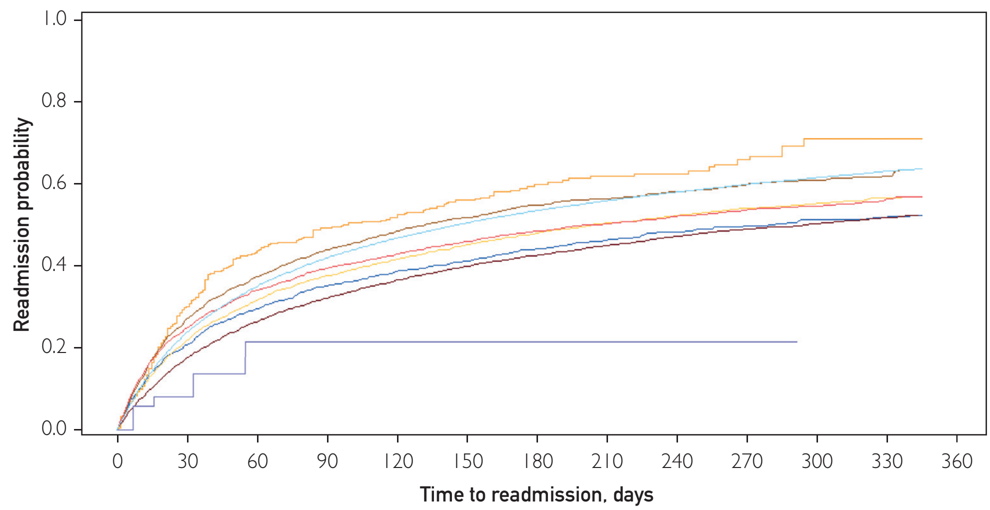
[a]DRG = Diagnosis related group; AHRQ = Agency for Heathcare Research and Quality.

[b]Risk of mortality subclass is defined as the likelihood of in-hospital mortality on the basis of secondary diagnosis, age, principal diagnosis, and whether certain procedures were performed.[12]

[c]Severity of illness subclass is defined as the extent of organ system loss of function or physiologic decompensation and is used to predict increased resource use because of the comorbidities and acute illness.[12]

and 50.4 % were men; 35.8% of admissions were for patients with systolic HF, the average length of stay was 5.0 days, and 96.1% were residents of the state in which hospital care was received. Most patients, 42.3% and 36.5%, were categorized under moderate likelihood of dying or major likelihood of dying, respectively. This is defined as the likelihood of in-hospital mortality on the basis of secondary diagnosis, age, principal diagnosis, and whether certain procedures were performed.[12] The most readmissions any patient had within 1 year was 18. The top 10 most common comorbidities included hypertension (75.4%), diabetes mellitus (44.7%), renal failure (40.5%), chronic pulmonary disease (37.2%), deficiency anemia (29.2%), fluid and electrolyte disorders (28.9%), obesity (18.1%), hypothyroidism (16.4%), peripheral vascular disorders (11.8%), and depression (9.65%) (Table 2).[12]

Figure 1 illustrates the probability of readmission and the number at risk at each time point for subsets defined by the types of heart procedures performed at each admission. The procedures of interest included repair of the heart and pericardium; heart transplant; the placement of ventricular assist device, pacemaker, and automatic cardioverter/defibrillator; the implantation of leadless pressure



374	934	598	445	333	287	236	175	126	111	75	26	9
375	5577	3984	3212	2590	2203	1843	1400	1120	840	597	330	152
376	15374	10040	7707	6074	5013	4097	3245	2605	1955	1402	861	408
378	20420	14663	11820	9829	8275	6940	5730	4734	3708	2970	1665	844
379	45060	34379	28029	23375	19691	16459	13719	11164	8693	6443	3951	2019
382	66	33	18	8	4	4	2	2	2	2	0	0
396	22757	15364	11944	9785	8365	6934	5617	4451	3411	2511	1591	776
Other	4173728	2893899	2237039	1795709	1482515	1228188	1011353	817022	629467	454881	283803	143480

374: Repair of heart and pericardium — 375: Heart transplantation — 376: VADs — 378: Pacemakers
379: ICD — 382: Cardiomems™ — 396: ECMO — Other

FIGURE 1. Weighted Kaplan-Meier failure curve for proportion of readmission and number at risk for subsets defined by heart failure procedures performed at each admission. Each admission may be repeated if more than 1 procedure of interest was performed.

sensor (Cardiomems HF system, Abbott); and extracorporeal membrane oxygenation auxiliary to heart operation. A summary of *International Classification of Diseases, Ninth Revision, Clinical Modification* procedure codes for HF admissions can be found in Supplemental Table S2 (available online at http://www.mcpiqojournal.org). Readmission probabilities at 30 days in patients who underwent Cardiomems HF system implantation in the derivation and validation cohorts were 0 and 0.088, respectively. With the exception of the Cardiomems HF system implantation, Figure 1 shows a Kaplan-Meier curve for the proportion of readmission and number at risk stratified by procedure codes in both the derivation and validation cohorts. From Figure 2, it can be observed that patients who underwent the Cardiomems HF system implantation during admission had significantly lower rates of readmission at all time points (P=.047). Patients who received a right heart catheterization or right and left heart catheterization at admission had significantly lower readmission probability than those who received other procedures (P<.001) (Figure 3).

Multivariate analyses of factors predicting readmission for all patients with HF using a derivation cohort (2010-2012) can be found in Supplemental Table S3 (available online at http://www.mcpiqojournal.org). Parameters from the multivariate analysis with P<.01 were used to create the HF readmission scale, the values of which are tabulated in Table 3. Table 4 shows the probability of readmission at 30, 60, 90, and 180 days on the basis of the risk score. Figure 4 illustrates the ROC curve and AUC at each time point (30, 60, 90, 180 days, respectively) to assess the accuracy of the risk scale using the derivation cohort (2010-2012). Figure 5 illustrates the

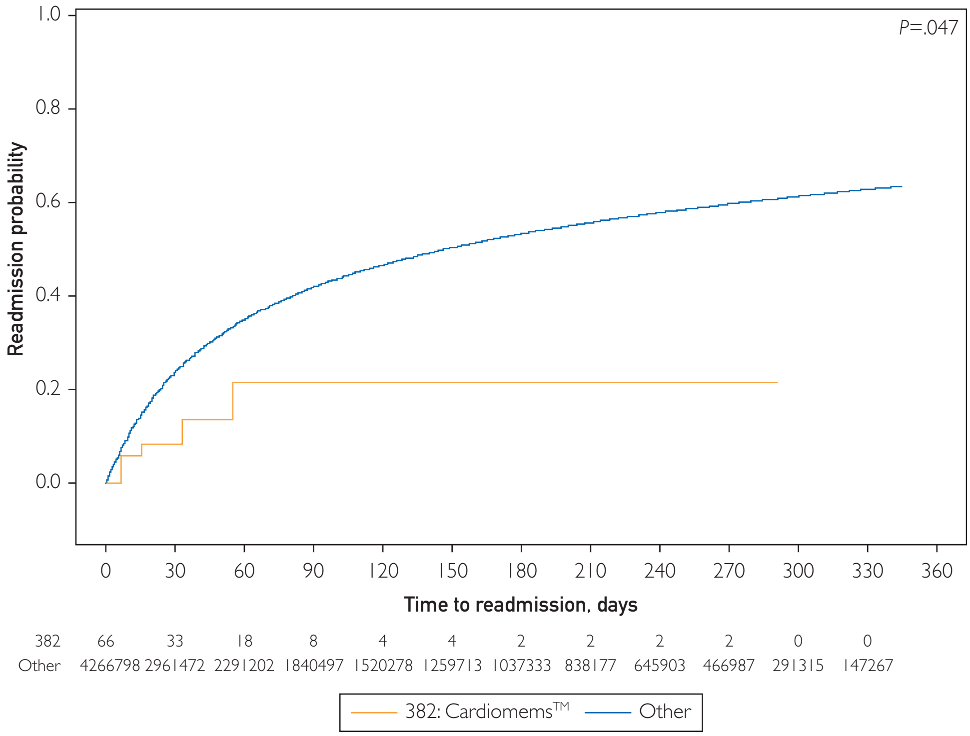


FIGURE 2. Weighted Kaplan-Meier failure curve for proportion of readmission and number at risk stratified by those who had undergone Cardiomems heart failure system implantation at each admission compared with those who had not.

ROC curve and AUC at each time point (30, 60, 90, 180 days, respectively) to assess the accuracy of the risk scale using the validation cohort (2013-2014).

DISCUSSION

In this study, we used a national database to generate a HF readmissions risk model that takes into account procedures performed at admission. It was observed that right heart catheterization and Cardiomems HF system implantation were protective factors against readmission, which is consistent with the current literature.[13-15] Our study also found reproducibility of the Readmission After Heart Failure scale by Chamberlain et al[9] despite the use of a different database with a larger population at different time points. Compared with the Readmission After Heart Failure scale, differences include the use of different databases (NRD vs SID), inclusion of HF surgical procedures, and incorporation of protective factors in our risk scale. Given the use of different databases and different timepoints, the respective models had similar AUC at all time intervals, which indicates the independence of time and similar predictions of readmission out through 180 days.

There exist many other HF prediction models with C-statistics ranging from poor to acceptable.[16] This points to the fact that HF is a disease with complex pathophysiology and is often quite difficult to predict. Two notable models include the ones by Keenan et al[17] and Krumholtz et al,[18] on which the Centers for Medicare and Medicaid Services has based its readmission risk calculations, which provide risk-standardized readmission rates for hospital comparisons using the Medicare database.[19] These initial prediction models have paved the way for others to follow. In a multisite study looking at predictors of clinical outcomes in acute decompensated HF, a simplified scoring system

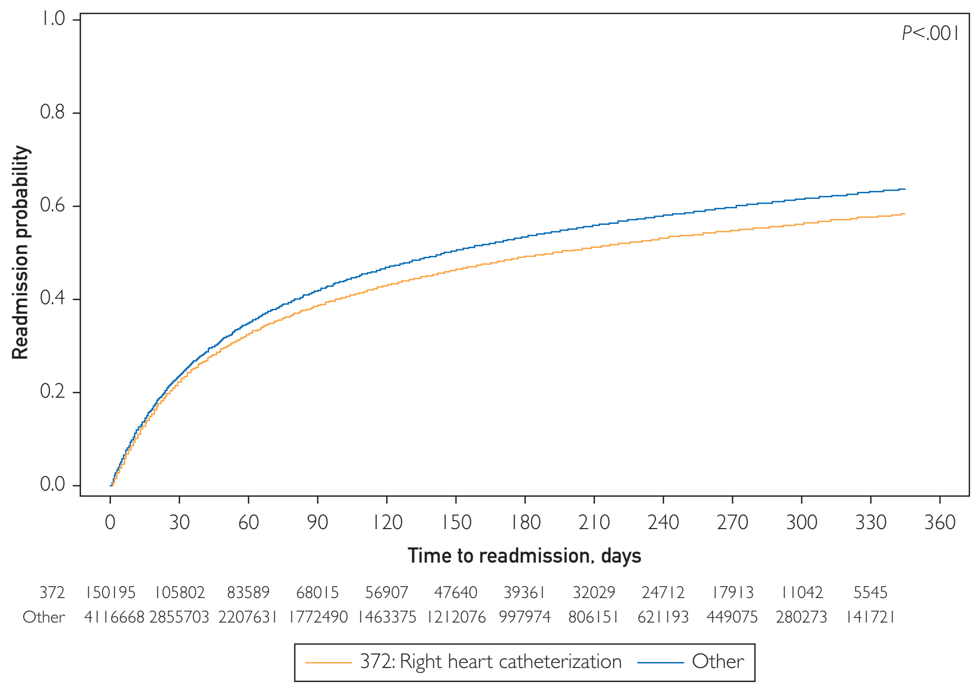


FIGURE 3. Weighted Kaplan-Meier failure curve for proportion of readmission and number at risk stratified by those who had undergone right heart catheterization or right and left heart catheterization at each admission compared with those who had not.

comprising only 5 commonly available clinical variables was able to discriminate the 30-day mortality risk from 0.5% to 53%.[20] Despite great efforts in developing readmission risk models, a study looking at trends in all-cause 30-day readmission rates among 70 US hospitals concluded that only slight improvements in the rates have been made, with only a handful of hospitals seeing significant improvement.[21] This points to the need for ongoing work.

To our knowledge, this is the first risk prediction model to include HF procedures. It was observed that, overall, the inclusion of certain HF procedures does not significantly affect our model. However, of note, patients who underwent a procedure for the placement of the Cardiomems HF system device were observed to have a significant decrease in readmission risk. This is consistent with the CHAMPION trial, which found that the use of the Cardiomems device has been shown to reduce HF hospitalizations and improve quality of life regardless of the ejection fraction.[13] Lastly, our model included protective factors (ie, factors that reduced the risk of readmission) not seen in other risk models. Protective factors in our model included alcohol use, obesity, heart transplant, permanent pacemaker placement, implantable cardioverter/defibrillator placement, and extracorporeal circulation.

An important limitation of this study is the lack of data on patient race in the database. According to a study examining racial and gender disparities in approximately 5.5 million HF admissions using the National Inpatient Sample database, Caucasians had the highest mortality rate (3.55%), whereas African Americans had the lowest mortality rate (1.75%); however, African Americans had a younger average age of admission than Caucasians (63 vs 77 years).[22] Moreover, the age-adjusted HF-related cardiovascular death rate and rate of hospitalization were approximately 2.5 times greater in African Americans than in Whites.[23] There exists clear evidence of health care disparities across race and

Mayo Clin Proc Inn Qual Out ■ June 2022;6(3):228-238 ■ https://doi.org/10.1016/j.mayocpiqo.2022.04.002
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TABLE 3. Values for Components of Heart Failure Readmissions Risk Scale Created Using Derivation Cohort

Characteristic	Point value
Age (y)	
0-39	4
40-49	3
50-59	2
60-69	2
70-79	1
80+	0
Median household income quartiles for patients by ZIP code	
Second/third/fourth	−1
Expected primary payer	
Medicaid	1
Private insurance	−3
Self-pay/no charge	−4
Other	−2
Length of stay (d)	
≤2	0
3-6	1
≥7	2
Comorbidities	
Acquired immune deficiency syndrome	3
Alcohol abuse	−1
Anemia	1
Arthritis, rheumatoid or collagen vascular disease	1
Chronic blood loss anemia	1
Congestive heart failure	1
Chronic lung disease	2
Depression	1
Diabetes mellitus, uncomplicated	1
Diabetes mellitus with chronic complications	1
Drug abuse	2
Liver disease	1
Lymphoma	1
Obesity	−1
Peripheral vascular disease	1
Psychoses	1
Renal failure	2
Solid tumor without metastasis	1
Procedures	
Heart replacement procedure	−3
Pacemaker placement	−1
Procedures, continued	
Automatic cardioverter/defibrillator placement	−3
Extracorporeal circulation and procedure auxiliary to heart operation	−1

Continued on next column

ethnicity in HF. Although it could be attributed to health care access and socioeconomic status, genetic susceptibility, social determinants of health, and implicit bias may also explain such disparities. Another limitation of this study is inherent to its retrospective nature.

Future studies are needed to properly validate the model presented here by applying it prospectively in both a single-institution and multicenter design to identify high-risk patients to target preventative

TABLE 4. Probability of Readmission by 30, 60, 90, and 180 days in the Validation Cohort Estimated on the Basis of Weighted Kaplan-Meier Failure Curve

Risk score	Day 30	Day 60	Day 90	Day 180
−7 to −5	8%	15%	19%	28%
−4	10%	16%	21%	30%
−3	13%	19%	23%	32%
−2	13%	20%	24%	32%
−1	15%	23%	28%	37%
0	16%	24%	30%	41%
1	18%	27%	33%	44%
2	19%	29%	36%	47%
3	21%	32%	39%	50%
4	23%	35%	42%	54%
5	25%	38%	45%	57%
6	28%	41%	49%	60%
7	30%	44%	52%	64%
8	33%	47%	55%	67%
9	35%	49%	58%	70%
10	38%	53%	60%	73%
11	41%	57%	65%	76%
12	46%	62%	69%	80%
13	46%	57%	65%	77%
14-16	56%	68%	77%	89%

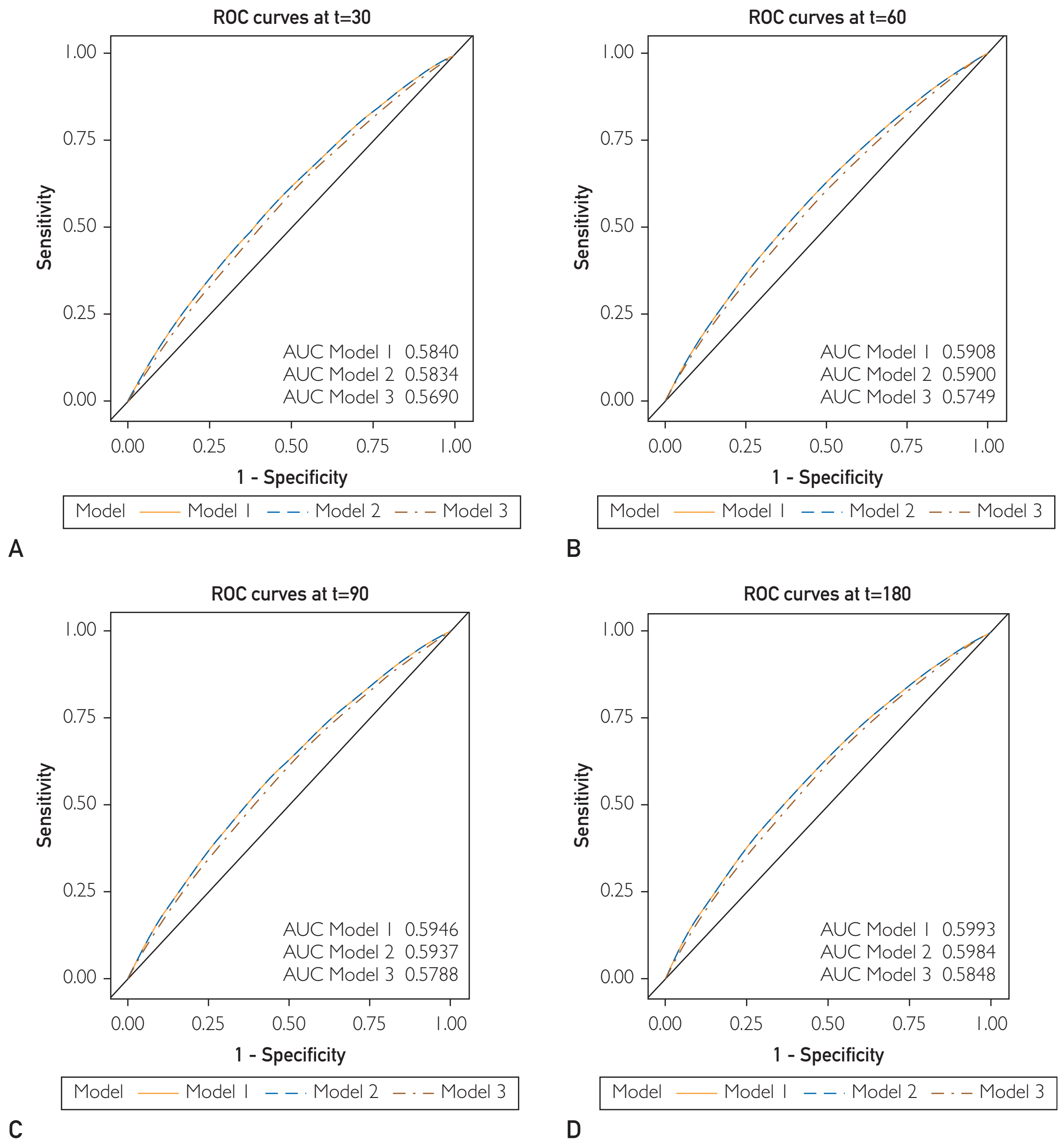

FIGURE 4. A-D, Receiver operating characteristic curve (ROC) and area under the ROC curve at each time point (30, 60, 90, and 180 days) using the derivation cohort (year 2010-2012) to assess the accuracy of the risk scale. Model 1 was fitted using our risk scale from the model with procedure codes. Model 2 was fitted using our risk scale from the model without procedure codes. Model 3 was fitted using the Readmission After Heart Failure scale from Chamberlain et al.[9]

interventions. Further, effects of using the model should be explored to determine its clinical utility (eg, effect on the number of HF readmissions, health care costs, and general health of patients with HF).

CONCLUSION

Heart failure is a major public health issue in the United States and worldwide. Although various methods have been implemented in an effort to reduce mortality and HF

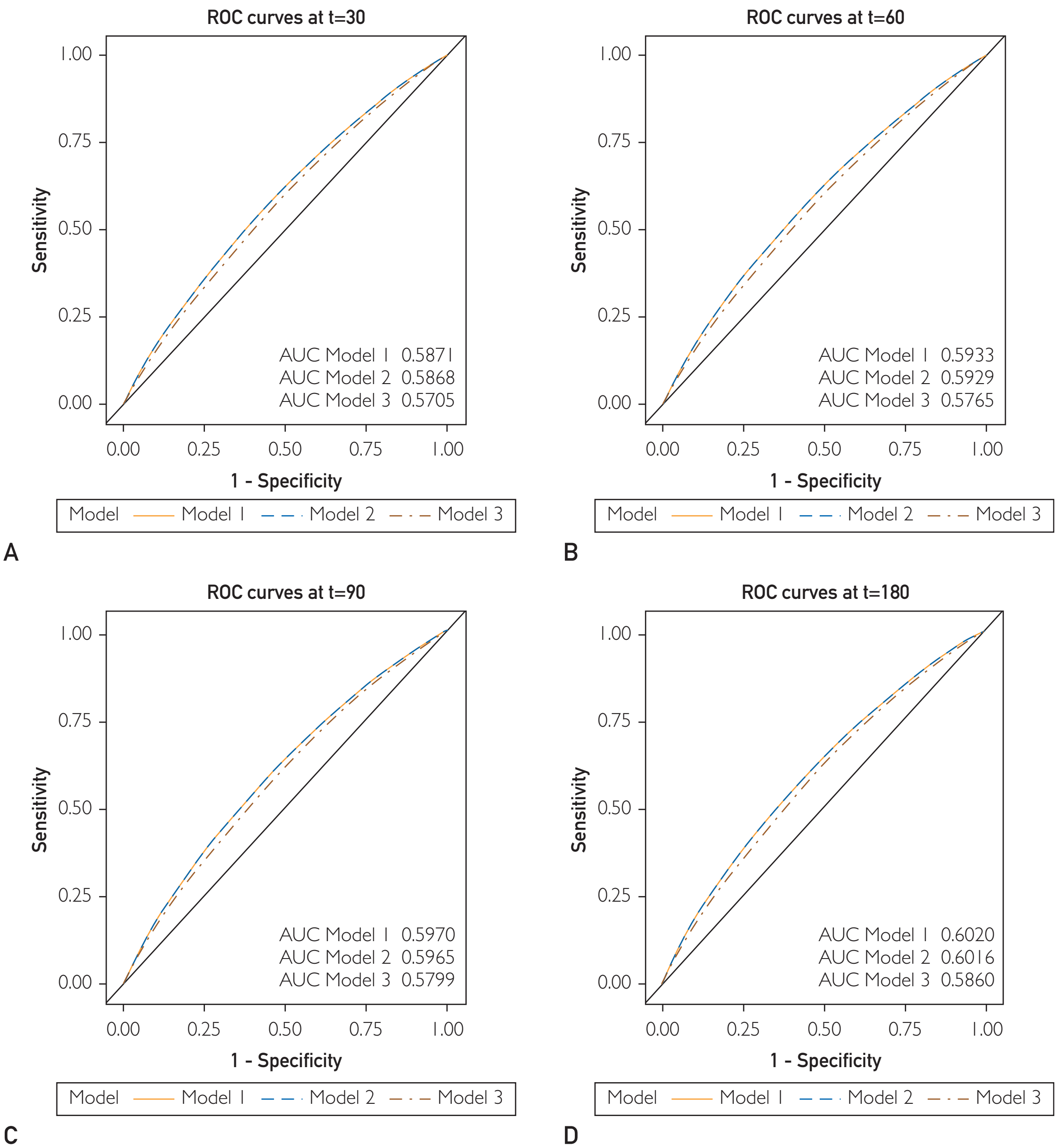

FIGURE 5. A-D, Receiver operating characteristic (ROC) curve and area under the ROC curve at each time point (30, 60, 90, and 180 days) using the validation cohort (year 2013-2014) to assess the accuracy of the risk scale. Model 1 was fitted using our risk scale from model with procedure codes. Model 2 was fitted using our risk scale from model without procedure codes. Model 3 was fitted using the Readmission After Heart Failure scale from Chamberlain et al.[9]

readmissions, such as the enactment of the Hospital Readmissions Reduction Program under the Affordable Care Act and development of various prediction models, it remains a significant burden on patients with HF and the health care system. Thus, establishing a useful risk model can identify those at high risk of readmission and provide a point-of-care tool to guide clinical decision making, reduce health care cost, guide appropriate use of resources, and improve health care outcomes. Our risk prediction model, which has been shown to be independent of both time and databases, may aid in reducing HF readmissions and guide specific interventions to lower the mortality rate.

SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at http://www.mcpiqojournal.org. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data.

Abbreviations and Acronyms: **AUC,** area under the curve; **HF,** heart failure; **NRD,** Nationwide Readmissions Database; **ROC,** receiver operating characteristic; **SID,** State Inpatient Database

Potential Competing Interests: The authors report no competing interests.

Correspondence: Address to David L. Joyce, MD, MBA, Division of Cardiothoracic Surgery, Department of Surgery, Medical College of Wisconsin, 8701 Watertown Plank Rd, Milwaukee, WI 53226 (djoyce@mcw.edu).

ORCID

Lillian Zheng: https://orcid.org/0000-0001-9894-1762; Nathan J. Smith: https://orcid.org/0000-0002-5443-9962; Aniko Szabo: https://orcid.org/0000-0002-8129-0614

REFERENCES

1. Virani SS, Alonso A, Benjamin EJ, et al. Heart disease and stroke statistics-2020 update: a report from the American Heart Association. *Circulation*. 2020;141(9):e139-e596. https://doi.org/10.1161/CIR.0000000000000757.
2. Huffman MD, Berry JD, Ning H, et al. Lifetime risk for heart failure among white and black Americans: cardiovascular lifetime risk pooling project. *J Am Coll Cardiol*. 2013;61(14):1510-1517. https://doi.org/10.1016/j.jacc.2013.01.022.
3. National Health and Nutrition Examination Survey Homepage. *Centers for Disease Control and Prevention*. https://www.cdc.gov/nchs/nhanes/index.htm. Accessed March 24, 2021.
4. Heidenreich PA, Albert NM, Allen LA, et al. Forecasting the impact of heart failure in the United States: a policy statement from the American Heart Association. *Circ Heart Fail*. 2013;6(3):606-619. https://doi.org/10.1161/HHF.0b013e318291329a.
5. Allen LA, Fonarow GC, Liang L, et al. Medication initiation burden required to comply with heart failure guideline recommendations and hospital quality measures. *Circulation*. 2015;132(14):1347-1353. https://doi.org/10.1161/CIRCULATIONAHA.115.014281.
6. Mortality Multiple Cause-of-Death Public Use Record. Centers for Disease Control and Prevention. https://www.cdc.gov/nchs/data/dvs/Multiple-Cause-Record-Layout-2019-508.pdf. Accessed March 24, 2021.
7. Report to the Congress: Medicare and the Health Care Delivery System. Refining the hospital readmissions reduction program, chapter 4. 2013. Accessed April 23, 2021. http://www.medpac.gov/chapters/Jun13_Ch04.pdf.
8. Elixhauser A, Steiner C. Readmissions to U.S. Hospitals by Diagnosis, 2010, *HCUP Statistical Brief #153*. Rockville, MD: Agency for Healthcare Research and Quality; 2013. http://www.hcup-us.ahrq.gov/ reports/statbriefs/sb153.pdf. Accessed April 23, 2021.
9. Chamberlain RS, Sond J, Mahendraraj K, Lau CS, Siracuse BL. Determining 30-day readmission risk for heart failure patients: the Readmission After Heart Failure scale. *Int J Gen Med*. 2018;11:127-141. https://doi.org/10.2147/IJGM.S150676.
10. NRD overview. Agency for Healthcare Research and Quality. https://www.hcup-us.ahrq.gov/nrdoverview.jsp. Accessed March 25, 2021.
11. Uno H, Cai T, Tian L, Wei LJ. Evaluating prediction rules for *t*-year survivors with censored regression models. *J Am Stat Assoc*. 2007;102(478):527-537. https://doi.org/10.1198/016214507000000149.
12. Averill RF, Goldfield NI, Muldoon J, Steinbeck BA, Grant TM. A closer look at all-patient refined DRGs. *J AHIMA*. 2002;73(1):46-50.
13. Adamson PB, Abraham WT, Aaron M, et al. CHAMPION trial rationale and design: the long-term safety and clinical efficacy of a wireless pulmonary artery pressure monitoring system. *J Card Fail*. 2011;17(1):3-10. https://doi.org/10.1016/j.cardfail.2010.08.002.
14. Assaad M, Sarsam S, Naqvi A, Zughaib M. CardioMems® device implantation reduces repeat hospitalizations in heart failure patients: a single center experience. *JRSM Cardiovasc Dis*. 2019;8:2048004019833290. https://doi.org/10.1177/2048004019833290.
15. Leung CC. Current role of the CardioMEMS device for management of patients with heart failure. *Curr Cardiol Rep*. 2019;21(9):98. https://doi.org/10.1007/s11886-019-1194-9.
16. Mahajan SM, Heidenreich P, Abbott B, Newton A, Ward D. Predictive models for identifying risk of readmission after index hospitalization for heart failure: a systematic review. *Eur J Cardiovasc Nurs*. 2018;17(8):675-689. https://doi.org/10.1177/1474515118799059.
17. Keenan PS, Normand SLT, Lin Z, et al. An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. *Circ Cardiovasc Qual Outcomes*. 2008;1(1):29-37. https://doi.org/10.1161/CIRCOUTCOMES.108.802686.
18. Krumholz HM, Parent EM, Tu N, et al. Readmission after hospitalization for congestive heart failure among medicare beneficiaries. *Arch Intern Med*. 1997;157(1):99-104. https://doi.org/10.1001/archinte.1997.00440220103013.
19. Hospital-Wide (All-Condition) 30-Day Risk-Standardized Readmission Measure. https://cpb-us-e1.wpmucdn.com/sites.dartmouth.edu/dist/6/2015/files/2018/08/mmshospital-wideall-conditionreadmissionrate-z6qxhh.pdf. Accessed April 5, 2022.
20. Khazanie P, Heizer GM, Hasselblad V, et al. Predictors of clinical outcomes in acute decompensated heart failure: Acute Study of Clinical Effectiveness of Nesiritide in Decompensated Heart Failure outcome models. *Am Heart J*. 2015;170(2):290-297. https://doi.org/10.1016/j.ahj.2015.04.006.
21. Bergethon KE, Ju C, DeVore AD, et al. Trends in 30-day readmission rates for patients hospitalized with heart failure: findings from the Get With The Guidelines-Heart Failure Registry. *Circ Heart Fail*. 2016;9(6):e002594. https://doi.org/10.1161/CIRCHEARTFAILURE.115.002594.
22. Tandon V, Stringer B, Conner C, et al. An observation of racial and gender disparities in congestive heart failure admissions using the National Inpatient Sample. *Cureus*. 2020;12(10):e10914. https://doi.org/10.7759/cureus.10914.
23. Nayak A, Hicks AJ, Morris AA. Understanding the complexity of heart failure risk and treatment in black patients. *Circ Heart Fail*. 2020;13(8):e007264. https://doi.org/10.1161/CIRCHEARTFAILURE.120.007264.