

ORIGINAL ARTICLE

Clinical Model to Predict 90-Day Risk of Readmission After Acute Myocardial Infarction

A Report From the National Cardiovascular Data Registry ACTION Registry

See Editorial by McCarthy and Pandey

BACKGROUND: Readmissions within 30 days after acute myocardial infarction have been used as a performance metric for hospitals. However, evolving concepts of value-based reimbursement have shifted the focus to 90 days after hospital discharge. Tools are needed to determine risk for 90-day readmission to identify patients who might benefit from enhanced transitional healthcare resources.

METHODS AND RESULTS: In this cohort study, we identified all Medicare beneficiaries with a primary diagnosis of acute myocardial infarction who were discharged from hospitals participating in National Cardiovascular Data Registry ACTION registry between 2008 and 2014. Among a random 70% sample (derivation cohort), we performed hierarchical proportional hazards regression, accounting for death as a competing risk, to assess predictors of all-cause readmission within 90 days. Models were validated in the remaining 30%. Among 86 849 unique patients, 23 912 (27.5%) were readmitted within 90 days. Of the readmissions, 55% occurred within 30 days and 81% occurred within 60 days. Predictors of readmission included older age and a history of diabetes mellitus or heart failure. Coronary revascularization was associated with a lower risk of readmission. A simple risk score incorporating patient demographic and clinical characteristics known before discharge identified groups of patients with readmission risks ranging from 13.1% to 42.9%. Model discrimination was moderate (C statistic=0.662), and calibration was excellent (slope=0.97, intercept=-0.04).

CONCLUSIONS: Readmission within 90 days of hospitalization for acute myocardial infarction can be predicted by variables known before discharge and offers the potential to prospectively design transitional care to the risks of individual patients.

Vinay Kini, MD, MSHP
Pamela N. Peterson, MD, MSPH
John A. Spertus, MD, MPH
Kevin F. Kennedy, MS
Suzanne V. Arnold, MD
Jason H. Wasfy, MD, MPhil
Jeptha P. Curtis, MD
Steven M. Bradley, MD, MPH
Amit P. Amin, MD
P. Michael Ho, MD, PhD
Frederick A. Masoudi, MD, MSPH

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WHAT IS KNOWN

- Readmissions within 30 days of acute myocardial infarction have been used as a performance metric for hospitals, but new episode payment models have shifted the focus to 90 days after hospital discharge.
- Hospitals and clinicians need tools to determine risk of 90-day readmission to identify patients who might benefit from enhanced transitional care resources.

WHAT THE STUDY ADDS

- Nearly 28% of patients hospitalized with acute myocardial infarction are readmitted within 90 days of discharge, with a large proportion occurring between 30 and 90 days (45% of total readmissions).
- The distribution of readmission risk was wide (ranging from 13% to 50% between the lowest and highest deciles of risk), and predictors of readmission included older age and complications such as heart failure.
- A simple risk score incorporating patient demographic and clinical characteristics known before discharge identified groups of patients at low (13%) and high (43%) risk of readmission.

Cardiovascular health care is moving from reimbursement based on volume to that based on value (ie, lowering healthcare costs while maintaining or improving health outcomes).¹⁻³ This transition will shift the risk of variations in costs and quality of care from insurers to hospitals and clinicians. A critical component of this transformation is the implementation of episode payment models (EPMs) that pay hospitals a fixed amount for all healthcare services provided within an episode of care. A voluntary EPM for acute myocardial infarction (AMI) recently announced by the Centers for Medicare and Medicaid Services (CMS) uses a time horizon of 90 days, which represents a substantial departure from both current fee-for-service models and 30-day penalties for readmission that have recently been implemented.⁴⁻⁶

Episode-based payment will require clinicians and hospitals to develop novel strategies to improve quality of care not only during a hospitalization but also in the period after discharge. Because nearly 20% of patients hospitalized with AMI are readmitted to a hospital shortly after discharge,^{7,8} readmissions are likely to play a large role in care management of AMI patients in EPMs. It is estimated that 22% and 12% of the costs within 90 days of an AMI are incurred from readmissions for patients who are managed with medical and percutaneous coronary intervention (PCI) strategies, respectively.⁹ However, little is known about the frequency and timing of 90-day readmissions, or how to prospectively identify patients at greater risk for 90-day readmission.

To succeed in these new EPMs, clinicians and hospitals need tools that can be used to assess the risk of 90-day readmission during a patient's index hospitalization for AMI, so that the intensity of follow-up, such as home health services, can be targeted to patient risk.¹⁰⁻¹⁴ To help hospitals identify their patients 90-day readmission risks, we used data from the National Cardiovascular Data Registry (NCDR) ACTION Registry¹⁵ to develop a clinically useful prediction model to assess the risk of readmission using data available before discharge.

METHODS

Data Source

The American College of Cardiology NCDR programs are designed to support efforts to improve the quality of cardiovascular care.¹⁶ In this study, we used NCDR ACTION Registry, a clinical database of patients hospitalized with AMI. More than a quarter of all hospitals caring for patients with AMI in the United States participate in the registry. ACTION uses a data quality program consisting of (1) a data quality report, (2) a set of internal quality metrics, and (3) a yearly data audit program designed to ensure completeness, consistency, and accuracy of collected data.¹⁶ Data not meeting these quality standards are excluded from registry analyses. Records of Medicare beneficiaries in ACTION are linked to claims collected by CMS, including data on subsequent outcomes including hospital readmissions and death through probabilistic matching. This study was prepared in compliance with the Strengthening of Reporting of Observational Studies in Epidemiology guidelines. The data, analytic methods, and study materials are stored at the NCDR and will be made available to other researchers for purposes of reproducing the results or replicating the procedure on request and peer review approval by the ACTION Research and Publications Committee.

Study Population

All Medicare beneficiaries hospitalized with AMI in NCDR ACTION registry from 2008 to 2014 were considered. We excluded patients at hospitals without >70% match on data elements used to link subsequent claims (ie, site-specific inability to match using patient social security numbers), patients who had no beneficiary link, and Medicare Advantage patients because billing data for those enrolled in health maintenance organizations are not included in longitudinal claims. We also excluded patients discharged to hospice, those who died during hospitalization, patients transferred to a different acute care facility, and those leaving the hospital against medical advice. Finally, we excluded patients with data collected on the short form in ACTION, given lack of sufficient data elements to predict readmission.

Primary Outcome and Potential Predictors

Our primary outcome measure was the first all-cause readmission to any hospital within 90 days of the index

hospitalization for AMI. Patient-level characteristics tested for inclusion in the model were chosen based on clinical rationale and prior studies of 30-day readmissions and included demographics (age, sex, and race/ethnicity), admission characteristics (means of transport to facility and insurance payer), cardiac status at first medical contact (ST-segment–elevation versus non–ST-segment–elevation myocardial infarction, heart rate and blood pressure, and heart failure [HF]), history and risk factors (smoking status, diabetes mellitus, hypertension, atrial fibrillation, cancer, stroke, prior AMI, prior HF, prior coronary revascularization), cardiac markers (initial troponin, creatinine, and hemoglobin), cardiac procedures and tests (coronary angiography, PCI, and coronary artery bypass surgery), and in-hospital clinical events (cardiogenic shock, suspected bleeding event, acute kidney injury, stroke, and HF). Hospital characteristics such as ownership and payer mix were not included as covariates to facilitate the utility of the risk models for clinicians at the bedside. Performance measures such as referral to cardiac rehab were not included in the model because inclusion in risk scores would likely serve as reminders to complete them rather than add to the discrimination of readmission risk. Finally, we collected data on primary readmission diagnosis codes, timing of readmissions, and 90-day mortality.

Statistical Analysis

Descriptive statistics were used to assess differences between patients who were (1) readmitted, (2) not readmitted and alive at 90 days after index hospitalization, and (3) not readmitted and died within 90 days. To develop and validate risk scores for readmission, we randomly selected 70% of patients as a model derivation cohort and the remaining 30% to a validation cohort. Using the derivation cohort, hierarchical proportional hazards regression models were estimated specifying a cumulative incidence function for readmission (ie, time to first readmission) and accounting for death as a competing risk according to methods described by Fine and Gray.¹⁷ Because our intent was to create parsimonious models useful to clinicians for bundled payments, we used backward selection procedures according to the method of Harrell.¹⁸ With this approach, the total adjusted variability (R^2) of an initial model considering all candidate variables was first estimated. Then, sequential backwards elimination was performed, with estimation of total model adjusted R^2 at each step. When the adjusted R^2 fell <90% of the R^2 of the initial model, the selection procedure was terminated and the remaining variables were retained in the final model. The discrimination (C statistic) and calibration (slope and intercepts) of the derivation model were then tested in the validation cohort.¹⁹ The cohort was stratified into deciles of predicted risk of readmission to describe frequencies and distributions of risk. To facilitate the utility of the risk models for clinicians at the bedside as well as for automated decision support tools embedded within electronic health records, we created simplified risk scores for prediction of readmission.²⁰ All statistical analyses were performed using SAS Version 9.2. Analyses from ACTION are approved by Chesapeake Research Review, Inc, an independent institutional review board and conducted by the NCDR analytic center at Saint Luke's Mid America Heart Institute.

RESULTS

Study Population and Cohort Characteristics

We identified 234 668 Medicare beneficiaries over the age of 65 who were discharged alive with a primary diagnosis of AMI from 2008 to 2014 in the ACTION registry. After excluding patients at hospitals without a >70% probabilistic match ($n=104\,086$), patients without a beneficiary link ($n=11\,009$), and Medicare health maintenance organization beneficiaries ($n=32\,724$), our analytic cohort comprised 86 849 patients (Figure 1). Characteristics of the analytic cohort were similar to the 104 086 patients who were not able to be matched (Table in the [Data Supplement](#)).

Cohort characteristics are shown in Table 1. The mean (SD) age was 77 (8.0) years, 58% were men, and 91% were white. Of the 86 849 patients, 23 912 (27.5%) were readmitted within 90 days, and 8 212 (9.5%) died within 90 days. Of the patients who died, 4 275 (52.1%) experienced a readmission before death. Of the 23 912 patients who were readmitted, 7 811 (33%) experienced >1 readmission.

Patients who were readmitted were older (mean age, 78 versus 76 years; $P<0.001$). Women had a higher likelihood of being readmitted compared with men (29.9% versus 25.8% readmitted; $P<0.001$). Black patients were more likely to be readmitted compared with white patients (32.9% versus 27.1% readmitted; $P<0.001$). Patients who were readmitted also had a higher likelihood of ambulance transport to first facility (54% versus 46%; $P<0.001$), having HF at first medical contact (28% versus 16%; $P<0.001$), having comorbid conditions including diabetes mellitus (43% versus 34%; $P<0.001$) and prior HF (27% versus 15%; $P<0.001$), and experiencing in-hospital complications such as a bleeding event (5% versus 4%; $P<0.001$). Patients who were readmitted had a lower likelihood of undergoing diagnostic coronary

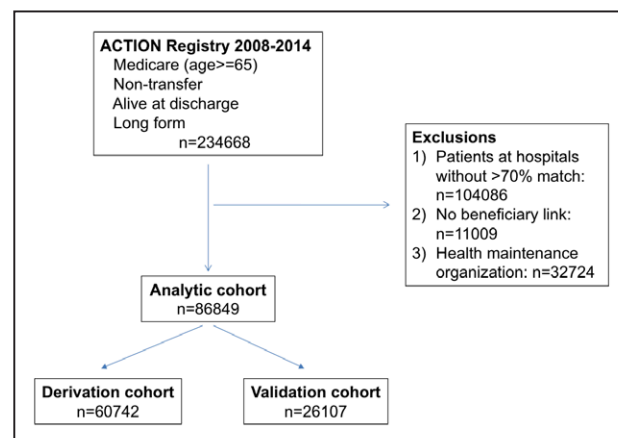


Figure 1. Study flow.

Cohort assembly for Medicare beneficiaries hospitalized with acute myocardial infarction from the National Cardiovascular Data Registry ACTION Registry.

Table 1. Characteristics of Patients Stratified by 90-Day Readmission and Mortality After Hospitalization for Acute Myocardial Infarction

	Total Study Cohort	Readmitted	Not Readmitted, Alive at 90 Days	Not Readmitted, Died Within 90 Days	P Value
	n=86 849	n=23 912	n=58 662	n=42 75	
Demographics					
Age, y	76.5±8.0	77.6±8.0	75.6±7.8	82.4±8.6	<0.001
Sex					<0.001
Male	50 178 (57.8%)	12 955 (54.2%)	35 070 (59.8%)	2 153 (50.4%)	
Female	36 671 (42.2%)	10 957 (45.8%)	23 592 (40.2%)	2 122 (49.6%)	
Body mass index	28.3±11.4	28.2±14.5	28.5±9.3	26.5±16.0	<0.001
Race					
White	78 902 (90.8%)	21 402 (89.5%)	53 628 (91.4%)	3 872 (90.6%)	<0.001
Black or African American	5 833 (6.7%)	1 921 (8.0%)	3 622 (6.2%)	290 (6.8%)	<0.001
Asian	1 103 (1.3%)	285 (1.2%)	762 (1.3%)	56 (1.3%)	0.446
American Indian or Alaskan Native	610 (0.7%)	202 (0.8%)	385 (0.7%)	23 (0.5%)	0.005
Native Hawaiian or Pacific Islander	119 (0.1%)	37 (0.2%)	73 (0.1%)	9 (0.2%)	0.232
Hispanic or Latino ethnicity	3 073 (3.5%)	887 (3.7%)	2 026 (3.5%)	160 (3.8%)	0.153
Admission					
Means of transport to first facility					<0.001
Self/family	43 878 (50.6%)	10 770 (45.1%)	31 810 (54.3%)	1 298 (30.4%)	
Ambulance	41 915 (48.3%)	12 877 (53.9%)	26 110 (44.6%)	2 928 (68.6%)	
Mobile ICU	352 (0.4%)	103 (0.4%)	225 (0.4%)	24 (0.6%)	
Air	621 (0.7%)	139 (0.6%)	462 (0.8%)	20 (0.5%)	
Location of first evaluation					<0.001
Emergency Department	63 163 (72.8%)	17 847 (74.7%)	41 757 (71.2%)	3 559 (83.3%)	
Cath Laboratory	7 710 (8.9%)	1 779 (7.4%)	5 755 (9.8%)	176 (4.1%)	
Other	15 919 (18.3%)	4 270 (17.9%)	11 111 (19.0%)	538 (12.6%)	
Insurance payor					
Private health insurance	48 553 (55.9%)	12 941 (54.1%)	33 403 (56.9%)	2 209 (51.7%)	<0.001
Medicare	86 849 (100.0%)	23 912 (100.0%)	58 662 (100.0%)	42 75 (100.0%)	
Medicaid	7 373 (8.5%)	2 490 (10.4%)	4 318 (7.4%)	565 (13.2%)	<0.001
Military health care	4 078 (4.7%)	956 (4.0%)	2 969 (5.1%)	153 (3.6%)	<0.001
State- specific plan	547 (0.6%)	144 (0.6%)	377 (0.6%)	26 (0.6%)	0.787
Indian health service	273 (0.3%)	98 (0.4%)	166 (0.3%)	9 (0.2%)	0.005
Non-US insurance	12 (0.0%)	2 (0.0%)	10 (0.0%)	0 (0.0%)	0.461
None	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	
Cardiac status on first medical contact					
First ECG obtained					0.633
Prehospital after	21 143 (24.4%)	5 839 (24.5%)	14 242 (24.3%)	1 062 (24.9%)	
First hospital arrival	65 565 (75.6%)	18 030 (75.5%)	44 336 (75.7%)	3 199 (75.1%)	
STEMI or STEMI equivalent	25 405 (29.3%)	6 179 (25.8%)	18 284 (31.2%)	942 (22.0%)	<0.001
Heart failure at first medical contact	16 978 (19.6%)	6 649 (27.8%)	8 469 (14.4%)	1 860 (43.5%)	<0.001
Heart rate at first medical contact	85.0±24.2	88.8±24.7	83.0±23.7	92.2±24.8	<0.001
Systolic blood pressure at first medical contact	146.0±33.1	144.2±33.4	147.8±32.7	131.3±33.6	<0.001
Cardiac arrest at first medical contact	1 347 (2.1%)	322 (1.9%)	899 (2.1%)	126 (4.1%)	<0.001
Cardiogenic shock at first medical contact	2 353 (2.7%)	713 (3.0%)	1 368 (2.3%)	272 (6.4%)	<0.001

(Continued)

Table 1. Continued

	Total Study Cohort	Readmitted	Not Readmitted, Alive at 90 Days	Not Readmitted, Died Within 90 Days	P Value
	n=86 849	n=23 912	n=58 662	n=42 75	
History and risk factors					
Current/recent smoker (within 1 y)	14 239 (16.4%)	3 854 (16.1%)	9 875 (16.8%)	5 10 (11.9%)	<0.001
Hypertension	71 980 (82.9%)	20 796 (87.0%)	47 605 (81.2%)	3 579 (83.7%)	<0.001
Dyslipidemia	59 328 (68.3%)	16 757 (70.1%)	39 944 (68.1%)	2 627 (61.5%)	<0.001
Currently on dialysis	2 600 (3.0%)	1 322 (5.5%)	1 073 (1.8%)	205 (4.8%)	<0.001
Chronic lung disease	16 749 (19.3%)	6 014 (25.2%)	9 512 (16.2%)	1 223 (28.6%)	<0.001
Diabetes mellitus	31 740 (36.6%)	10 360 (43.3%)	19 692 (33.6%)	1 688 (39.5%)	<0.001
Prior MI	25 336 (29.2%)	7 992 (33.4%)	15 931 (27.2%)	1 413 (33.1%)	<0.001
Prior heart failure	15 892 (18.3%)	6 513 (27.3%)	7 805 (13.3%)	1 574 (36.8%)	<0.001
Prior PCI	24 202 (27.9%)	7 161 (30.0%)	16 135 (27.5%)	906 (21.2%)	<0.001
Prior coronary artery bypass graft	17 670 (20.4%)	5 546 (23.2%)	11 254 (19.2%)	870 (20.4%)	<0.001
Atrial fibrillation or flutter	10 892 (12.6%)	3 914 (16.4%)	6 056 (10.3%)	922 (21.6%)	<0.001
Cerebrovascular disease	15 797 (18.2%)	5 573 (23.3%)	8 982 (15.3%)	1 242 (29.1%)	<0.001
Peripheral arterial disease	12 370 (14.2%)	4 527 (18.9%)	7 028 (12.0%)	815 (19.1%)	<0.001
Cocaine use	172 (0.2%)	47 (0.2%)	119 (0.2%)	6 (0.1%)	0.673
Comfort measures only	2 871 (3.3%)	472 (2.0%)	745 (1.3%)	1 654 (38.7%)	<0.001
Cardiac markers					
Initial creatinine value	1.4±1.2	1.6±1.4	1.3±1.0	1.8±1.5	<0.001
Glomerular filtration rate	62.8±31.5	57.2±32.8	65.9±29.5	51.5±40.9	<0.001
Initial hemoglobin value	13.1±2.1	12.6±2.2	13.5±2.0	12.0±2.2	<0.001
International Normalized Ratio value	1.2±0.9	1.3±0.9	1.2±0.9	1.4±1.0	<0.001
Initial troponin collected	1.1±0.3	1.1±0.3	1.1±0.3	1.1±0.3	0.206
Procedures and test					
Noninvasive stress testing	4 546 (5.2%)	1 438 (6.0%)	2 933 (5.0%)	175 (4.1%)	<0.001
Diagnostic coronary angiography	70 026 (80.7%)	17 663 (73.9%)	50 613 (86.3%)	1 750 (41.0%)	<0.001
PCI	47 444 (54.7%)	11 168 (46.7%)	35 323 (60.3%)	953 (22.3%)	<0.001
Coronary artery bypass graft surgery	7 656 (8.8%)	1 948 (8.2%)	5 569 (9.5%)	139 (3.3%)	<0.001
Events					
Reinfarction	570 (0.7%)	182 (0.8%)	342 (0.6%)	46 (1.1%)	<0.001
Cardiogenic shock	2 418 (2.8%)	795 (3.3%)	1 318 (2.2%)	305 (7.1%)	<0.001
Suspected bleeding event	3 481 (4.0%)	1 261 (5.3%)	1 985 (3.4%)	235 (5.5%)	<0.001
CVA/Stroke	641 (0.7%)	264 (1.1%)	259 (0.4%)	118 (2.8%)	<0.001
Heart failure	5 534 (6.4%)	2 130 (8.9%)	2 823 (4.8%)	581 (13.6%)	<0.001

Continuous variables compared using 1-way ANOVA. Categorical variables compared using χ^2 or Fisher exact test. ICU indicates intensive care unit; MI, myocardial infarction; PCI, percutaneous coronary intervention; and STEMI, ST-segment–elevation myocardial infarction.

angiography (74% versus 83%; $P<0.001$), PCI (47% versus 58%; $P<0.001$), or coronary artery bypass surgery (8% versus 9%; $P<0.001$) at index hospitalization for AMI.

Readmission Diagnosis and Timing

Of the 23 912 readmissions identified in the analytic cohort, 13 152 (55%) occurred within 30 days, and 19 369 (81%) occurred within 60 days (Figure 2). The

most common primary readmission diagnoses included congestive HF (16%), coronary atherosclerosis (11%), AMI (10%), and dysrhythmias (5%). A list of the 15 most common readmission diagnoses is provided in Table 2.

Risk Model Development and Validation

Seventy percent of the cohort were randomly assigned to the derivation cohort (n=60 742) and the remaining

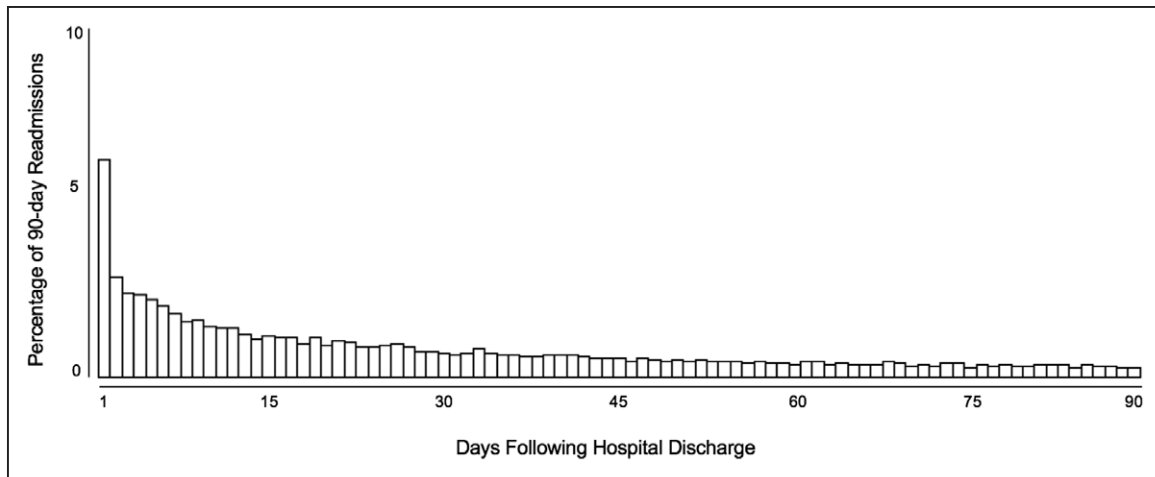


Figure 2. Timing of 90-day readmissions after hospitalization for acute myocardial infarction.

Of the 23 912 readmissions identified in the analytic cohort, 13 152 (55%) occurred within 30 days, and 19 369 (81%) occurred within 60 days.

30% to the validation cohort (n=26 107). There were no significant differences in characteristics between the derivation and validation cohorts. After multivariable adjustment and stepwise elimination, 12 variables were retained (Figure 3). Factors independently associated with a higher likelihood of readmission included age (hazard ratio, 1.12; 95% CI, 1.10–1.14 for each 10-year increase), HF at first medical contact (odds ratio [OR], 1.21; 95% CI, 1.17–1.26), heart rate at first medical contact (OR, 1.04; 95% CI, 1.03–1.04 for each 5 beats per minute increase), current dialysis (OR, 1.43; 95% CI, 1.32–1.54), diabetes mellitus (OR, 1.21; 95% CI, 1.17–1.25), history of HF (OR, 1.27; 95% CI, 1.22–1.32), cerebrovascular disease (OR, 1.16; 95% CI, 1.12–1.21), peripheral artery disease (OR, 1.18; 95% CI, 1.13–1.23), chronic lung disease (OR, 1.28; 95% CI,

1.24–1.33), and complications at the index hospitalization including a 5 unit drop in glomerular filtration rate (OR, 1.02; 95% CI, 1.02–1.02] and HF (OR, 1.32; 95% CI, 1.25–1.39). PCI at index hospitalization was associated with lower likelihood of readmission (OR, 0.89; 95% CI, 0.86–0.92).

In the validation cohort, model discrimination was moderate (C statistic=0.662) and calibration was excellent (slope=0.9728 and intercept=–0.038). A plot of the observed over expected rate of readmission is shown in Figure 4. There was a 4-fold difference in risk of readmission from the lowest (12.9%) to the highest (50.2%) deciles of risk.

The simplified risk score for 90-day readmission is shown in Figure 5. Patients in the lowest risk cohort (≤ 2 points) had a readmission risk of 13.1%, whereas

Table 2. Most Common Readmission Diagnoses

Diagnosis	Percent of Readmissions, Total	Percent of Readmissions, 1–30 Days	Percent of Readmissions, 31–60 Days	Percent of Readmissions, 61–90 Days
Congestive heart failure	15.7	17.0	13.7	13.4
Coronary atherosclerosis	11.1	10.8	13.0	9.3
Acute myocardial infarction	10.2	10.1	9.4	11.8
Dysrhythmias	5.4	5.7	5.3	4.7
Sepsis	3.6	3.8	3.5	3.4
Pneumonia	3.3	3.1	3.8	3.3
Other chest pain	3.0	3.2	2.6	2.6
Hemorrhage	2.6	2.9	2.2	2.2
Renal disease	2.6	2.7	2.6	2.4
Complications of device	2.3	2.4	2.1	2.4
Complications of procedure	2.2	2.8	1.3	0.9
Cerebrovascular disease	2.1	2.1	1.9	2.4
Heart valve disorder	1.0	0.9	1.3	0.9
Myocarditis	0.4	0.4	0.3	0.2
Conduction disorder	0.3	0.3	0.2	0.4

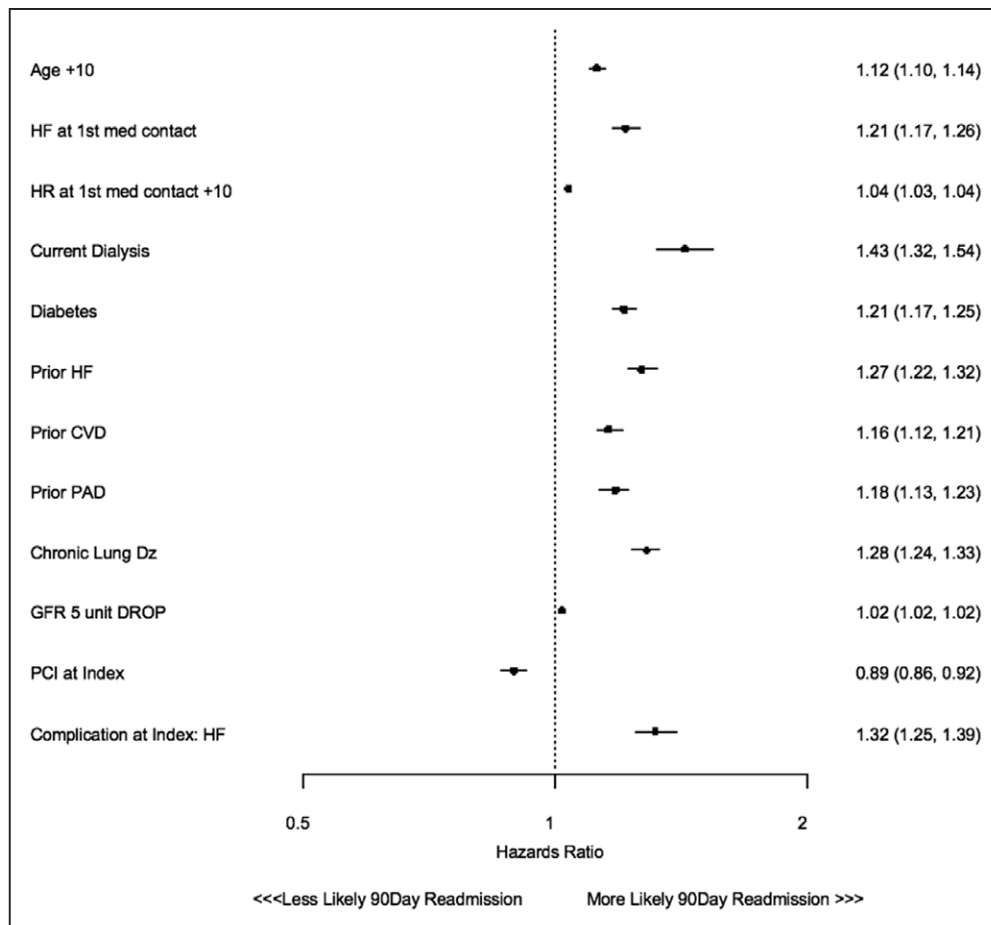


Figure 3. Variables retained in final prediction model for risk of 90-day readmission.

Hazard ratios and CIs for independent predictors of 90-day readmission. CVD indicates cerebrovascular disease; Dz, disease; GFR, glomerular filtration rate; HF, heart failure; PAD, peripheral arterial disease; and PCI, percutaneous coronary intervention.

patients in the highest risk cohort (≥ 11 points) had a readmission risk of 42.9%.

DISCUSSION

Summary of Findings

In this study, we report the development and validation of a clinically useful model to identify patients at high risk for 90-day readmission after hospitalization for AMI that can be used to help clinicians succeed in emerging EPMs. We found that although 27.5% of patients are readmitted within 90 days, the distribution of readmission risk is wide and ranges from 13% to 50% between the lowest and highest deciles of risk. The discriminatory ability of our model to predict readmission (C statistic=0.66) is similar to slightly higher compared with prior AMI readmission risk models (C statistic for CMS model=0.63),⁸ reflecting the feasibility of using clinically relevant variables available at the time of hospital discharge to identify patients at high risk of readmission. A main strength of this study is the evaluation of a 90-day (rather than 30-day) episode of AMI care

to coincide with recent proposals by CMS and other commercial insurance providers.^{5,6}

Extension of Prior Readmission Risk Models

Previous studies that have assessed the traditional 30-day period used in quality reporting have shown that $\approx 20\%$ of Medicare beneficiaries are readmitted within 30 days of AMI.^{7,8,21} We found that 28% of patients are readmitted within 90 days and that vulnerability for readmission remains high throughout the 90-day period, although most readmissions occur early and may be particularly amenable to transitional interventions. An important aspect of our study is the use of clinical data available during the index hospitalization to develop a risk model for readmission. Most readmission risk models, including the model employed by CMS, are performed at the hospital level and use retrospective administrative data to identify covariates that are included in the model.^{8,22} Using preadmission risk factors is important when trying to hold hospitals accountable for increased readmission

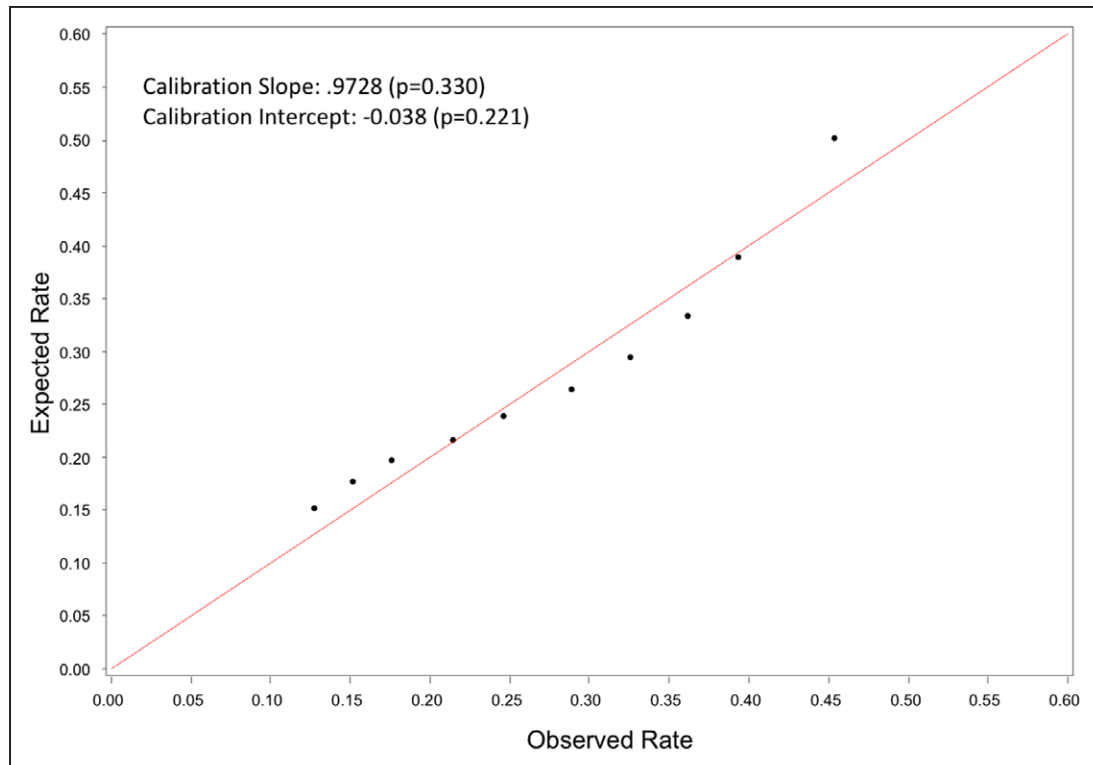


Figure 4. Observed over expected 90-day readmission in the validation cohort. Plot of the observed over expected rate of readmission. There was a 4-fold difference in risk of readmission from the lowest (12.9%) to the highest (50.2%) deciles of risk.

rates, but from the perspective of the hospital planning postdischarge care, it is important to consider in-hospital complications such as worsening renal function or HF in the risk model. The predictive power of some of these variables was strong, such as HF complication at index hospitalization. Moreover, our use of a clinical registry enabled us to include variables

that are not available in administrative data, such as hemodynamic condition at first medical contact. Performance of PCI was associated with a reduced likelihood of readmission and likely serves as an important marker of patient's condition associated with this treatment rather than a protective effect of undergoing coronary intervention.²³

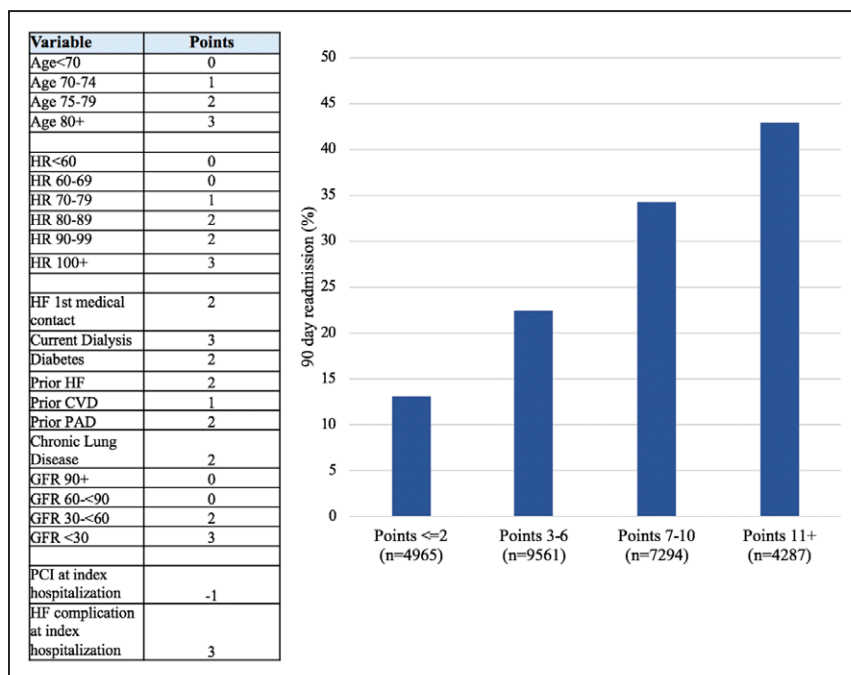


Figure 5. Simplified risk score for predicting 90-day readmission risk. A simple risk score incorporating patient demographic and clinical characteristics identified groups of patients with 90-day readmission risk after hospitalization for acute myocardial infarction (AMI) ranging from 13.1% to 42.9%. CVD indicates cerebrovascular disease; GFR, glomerular filtration rate; HF, heart failure; HR, heart rate at first medical contact; PAD, peripheral arterial disease; and PCI, percutaneous coronary intervention.

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EPMs and Transitional Care

Although a 30-day time period is currently used by CMS for public reporting and incentive programs to reduce readmission,²⁴ CMS recently announced the implementation of a voluntary 90-day EPM for AMI.⁵ As CMS and commercial insurance providers begin implementing 90-day EPMs, hospitals will need to deliver high-quality, efficient care that directs more transitional care resources to patients at the highest risk of postdischarge readmission. EPMs will provide a strong incentive for providers to develop novel strategies to assess and minimize the risk of costly complications including readmission given the wide variation in 90-day risk. Our risk model could help clinicians and hospitals succeed in EPMs by enabling targeting of interventions to patients at highest risk of readmission. For example, pre-discharge planning by a multidisciplinary care team, patient education about the importance of medication adherence and follow-up, intensive home health care, and call lines to cardiologists may all be useful in reducing the likelihood of readmission among high-risk patients.^{10–14} Some hospitals are experimenting with more creative approaches, such as using real-time video applications to conduct 1- and 3-day postdischarge virtual visits, or even doing 1-day postdischarge home nursing visits for patients at highest risk. Finally, our model may also be helpful for patients because awareness of high-risk status may motivate more frequent monitoring and checking in with their clinicians for follow-up. The ongoing application of risk scoring, coupled with further study on the impact of targeted interventions on outcomes and costs, will be important as the healthcare system continues to transition to reward value.

Limitations

Our study should be interpreted in the context of several limitations. First, we only included Medicare beneficiaries over the age of 65, which may limit the generalizability of our model. However, older patients tend to have higher risk of hospital readmission compared with younger patients.^{10,21} Second, we only included variables available from the ACTION registry, which could lead to unmeasured confounding, and the inclusion of additional variables, such as socioeconomic status or frailty, could further improve risk stratification for readmission and should be tested in future studies. Third, the external validity of our model is uncertain because our data were limited to hospitals participating in ACTION that may be more likely to participate in quality improvement efforts in general. Fourth, generalizability of our results may be limited because we excluded a large number of patients from hospitals without a >70% match to Medicare claims. However, the characteristics of our study cohort were similar to the patients that were excluded. Fifth, although the discriminatory capability of our model was moderate, the C statistic is similar to slightly higher than other

AMI readmission risk prediction models and was predictive over a 10-fold difference in readmission risk between deciles. Sixth, we considered only the first readmission in our risk prediction models because readmission risk prediction may occur each time a patient was hospitalized with AMI. Seventh, although prior HF, HF on first medical contact, and HF complication during index hospitalization were predictors of readmission, cardiogenic shock was not. This may have been because of the small number of patients with cardiogenic shock and insufficient power to detect a difference after multivariable adjustment.

Conclusions

We identified risk factors for readmission through 90 days after AMI discharge and created a model to identify patients at higher risk using variables known before discharge. Application of this model may improve value by enabling targeting of interventions to patients at highest risk of readmission.

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Correspondence

Vinay Kini, MD, MSHP, University of Colorado Anschutz Medical Campus, Mail Stop B130, Academic Office One, 12631 E, 17th Ave, Aurora, CO 80045. Email vinay.kini@ucdenver.edu

Affiliations

Division of Cardiology, University of Colorado Anschutz Medical Campus, Aurora (V.K., P.N.P., P.M.H., F.A.M.). Division of Cardiology, Saint Luke's Mid America Heart Institute/UMKC, Kansas City, MO (J.A.S., K.F.K., S.V.A.). Division of Cardiology at Massachusetts General Hospital, Harvard Medical School, Boston (J.H.W.). Yale University School of Medicine, New Haven, CT (J.P.C.). Division of Cardiology, Minneapolis Heart Institute (S.M.B.). Washington University School of Medicine, St Louis, MO (A.P.A.).

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