

Development and Validation of a Predictive Model for Short- and Medium-Term Hospital Readmission Following Heart Valve Surgery

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Background—Although models exist for predicting hospital readmission after coronary artery bypass surgery, no such models exist for predicting readmission after heart valve surgery (HVS).

Methods and Results—Using a geographically and structurally diverse sample of US hospitals (Premier Inpatient Database, January 2007–June 2011), we examined patient, hospital, and clinical factors predictive of short- and medium-term hospital readmission post-HVS. We set aside 20% of hospitals for model validation. A generalized estimating equation model accounted for clustering within hospitals. At 219 hospitals, we identified 38 532 patients (67 years, 56% male, 62% aortic valve surgery) who underwent HVS. A total of 3125 (7.8%) and 4943 (12.8%) patients were readmitted to the index hospital within 1 and 3 months, respectively. Our 3-month model predicted readmission rates between 3% and 6.1% with fair discrimination (C-statistic, 0.67) and good calibration (predicted vs observed differences in validation cohort averaged 1.9% across all deciles of predicted readmission risk). Results were similar for our 1-month model and our simplified 3-month model (suitable for clinical use), which used the 5 strongest predictors of readmission: transfused units of packed Red blood cells, presence of End-stage renal disease, type of Valve surgery, Emergency hospital admission, and hospital Length of stay (REVEaL).

Conclusions—We described and validated key factors that predict short- and medium-term hospital readmission post-HVS. These models should enable clinicians to identify individuals with HVS who are at increased risk for hospital readmission and are most likely to benefit from improved postdischarge care and follow-up. (*J Am Heart Assoc.* 2016;5:e003544 doi: 10.1161/JAHA.116.003544)

Key Words: aortic valve • mitral valve • model • prediction statistics • readmission • surgery

Preventing hospital readmission has become a national priority for hospitals in the United States. This is partially because many readmissions are believed to be preventable and

are a burden to patients, as well as hospitals.¹ Additionally, Medicare is now imposing a 3% financial penalty on hospitals with above-average readmission rates. Payment bundling is also becoming increasingly common among insurance carriers as a method to share financial risk with hospitals. In particular, the Affordable Care Act specifically requires Medicare to test 90-day bundled payments, particularly for procedure-related hospitalizations such as coronary artery bypass grafting (CABG) and heart valve surgery (HVS),² such that hospitals will be financially responsible for any readmission within 90 days after hospital discharge. As a result, there is a growing need to estimate the risk for readmission with improved accuracy, so that hospitals can better focus and intervene in patients at highest risk of readmission and thereby improve quality of care and decrease costs.

Although the risk factors for hospital readmission has previously been explored for patients undergoing CABG,^{3–6} only 1 previous European study has examined patients with HVS,⁷ and no predictive models have specifically evaluated medium-term (90-day) readmission. Given that more than 80 000 Americans undergo HVS annually⁸ and this number is increasing,⁹ there is a sizable population that would benefit

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from improved readmission risk prediction. Because the procedures and pathology are substantially different between patients who require CABG versus HVS, there are likely to be important differences in risk factors for hospital readmission in patients with HVS. As a result, we aimed to create and validate models that would estimate risk for hospital readmission for both short- and medium-term time frames. We further aimed to create a simplified clinical model suitable for bedside use by health care providers at the time of hospital discharge.

Methods

Design, Setting, and Subjects

We identified patients discharged from US hospitals that contributed to the Premier Healthcare Alliance Inpatient Database (Premier, Inc., Charlotte, NC).¹⁰ Premier, Inc., is an alliance of a geographically and structurally diverse group of US hospitals that share anonymized cost-accounting data for improving the quality, safety, and value of care. The Premier database captures ≈15% to 20% of inpatient US hospitalizations annually. Unlike administrative databases that contain only sociodemographic, diagnostic, and procedure codes assigned at the time of discharge, Premier also contains date-stamped hospital service codes for medications, procedures, diagnostic tests, and therapeutic services. The hospital data extracts undergo rigorous quality checks before being added to the database, and therefore there are rarely any issues stemming from missing or incomplete data. The data are fully de-identified, and so the Institutional Review Board at Baystate Medical Center determined that this study did not constitute human subjects research.

We included all patients hospitalized with an International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) procedure code for HVS (35.10, 35.11, 35.12, 35.13, 35.21, and 35.22) between January 2007 and June 2011. Patients undergoing concurrent CABG (36.1x), transcatheter aortic valve replacement, and mitral-clip surgery were excluded. We excluded patients with isolated tricuspid and/or pulmonic valve surgery because these procedures were rare (<1%) and the pathophysiological processes of these diseases are very different from that of the aortic and mitral valve surgery. However, pulmonary and tricuspid valve surgeries (35.13, 35.14, 35.23, and 35.24) were included if performed in combination with a mitral or aortic HVS. We excluded patients who died in the hospital or were of unknown sex. We further excluded patients who were transferred to another inpatient facility because we could not follow their clinical course or assess for other hospital management and outcomes. We then grouped patients into 3 surgical categories to allow comparison of readmission risk

across surgical type and complexity: isolated aortic valve, isolated mitral valve, and a combination group. The combination group included aortic+mitral, aortic+tricuspid/pulmonic, or mitral+tricuspid/pulmonic.

We included demographic data, such as age, sex, race/ethnicity, and insurance status, for each admission and included 29 individual comorbidity indicators based on methods developed by Elixhauser et al.¹¹ Hospital characteristics included size, teaching status, urban versus rural setting, census region, and annualized hospital cardiac surgical volume, which included both HVS and CABG.

Because the goal of our predictive model was to create a clinically applicable model that could predict hospital readmission, we also included various aspects of the hospital clinical course that could influence readmission risk. Inclusion of these treatment factors and hospital complications makes this model inappropriate for hospital profiling and causal estimation. Rather, this model uses all available variables in an attempt to provide the best model to predict readmission, regardless of causation. Specifically, we included the number of packed red blood cells (PRBCs) transfused during the hospitalization, number of days spent in the intensive care unit, number of days with invasive mechanical ventilation, receipt of physical therapy, receipt of cardiac rehabilitation, and total hospital length of stay. We also used present on admission codes to identify postoperative infections, including pneumonia, cellulitis, mediastinitis, urinary tract infection, sepsis, catheter-associated infection, and *Clostridium difficile* (Table 1).

Outcome Measures

Our primary study outcome was readmission to the hospital that performed the primary surgical procedure, at any time

Table 1. ICD-9 Codes for Infection, Not Present on Admission

Infection Diagnosis	ICD-9 Code
Sepsis	038.x, 790.7, 995.91, 995.92, 785.52
Pneumonia	480.x, 481.x, 482.x, 483.x, 484.x, 485.x, 486.x, 487.x, 488.x
Cellulitis	682.2, 682.6, 682.8, 682.9
Mediastinitis	519.2
Urinary tract infection	599.0, 112.2
<i>Clostridium difficile</i>	8.45
Device-related infection	996.61, 999.31, 996.62, 996.69, 996.64

ICD-9 indicates International Classification of Diseases, Ninth Revision.

Table 2. Baseline Patient Characteristics by 3-Month Readmission Status

Factor	Readmission, N (%)	No Readmission, N (%)	P Value*
	(N=4943)	(N=33 589)	
Age, mean±SD, y	65.8 (14.2)	64.8 (13.9)	<0.001
Age group, y			<0.001
18–24	30 (0.6)	272 (0.8)	
25–34	112 (2.3)	738 (2.2)	
35–44	279 (5.6)	1969 (5.9)	
45–54	666 (13.5)	4533 (13.5)	
55–64	926 (18.7)	7553 (22.5)	
65–74	1298 (26.3)	8934 (26.6)	
75–84	1357 (27.5)	8227 (24.5)	
85+	275 (5.6)	1363 (4.1)	
Male sex	2519 (51)	18 859 (56.1)	<0.001
Race/ethnicity			<0.001
White	3407 (68.9)	24 088 (71.7)	
Black	500 (10.1)	2190 (6.5)	
Hispanic	230 (4.7)	1164 (3.5)	
Other	806 (16.3)	6147 (18.3)	
Marital status			<0.001
Married	2492 (50.4)	18 442 (54.9)	
Single	1944 (39.3)	11 845 (35.3)	
Other/missing	507 (10.3)	3302 (9.8)	
Insurance payer			<0.001
Medicare	3021 (61.1)	18 130 (54)	
Medicaid	342 (6.9)	1764 (5.3)	
Managed care/commercial indemnity	1343 (27.2)	11 806 (35.1)	
Self-pay/other	237 (4.8)	1889 (5.6)	
Admission type			<0.001
Emergency	1232 (24.9)	4586 (13.7)	
Urgent	706 (14.3)	4701 (14)	
Elective	3005 (60.8)	24 302 (72.4)	
Valve surgeries			<0.001
Mitral valve surgery	1658 (33.5)	10 401 (31.0)	
Aortic valve surgery	2810 (56.8)	21 041 (62.6)	
Combination surgery	475 (9.6)	2147 (6.4)	
Length of stay, median (IQR), days [†]	10 (7–17)	7 (5–11)	<0.001

Continued

Table 2. Continued

Factor	Readmission, N (%)	No Readmission, N (%)	P Value*
	(N=4943)	(N=33 589)	
Length of stay (min–max, days)			<0.001
Quartile 1 (1–5)	692 (14)	9181 (27.3)	
Quartile 2 (6–7)	899 (18.2)	8347 (24.9)	
Quartile 3 (8–12)	1372 (27.8)	8808 (26.2)	
Quartile 4 (13–244)	1980 (40.1)	7253 (21.6)	
Elixhauser comorbidities			
Congestive heart failure	2153 (43.6)	10 878 (32.4)	<0.001
Valvular disease	163 (3.3)	482 (1.4)	<0.001
Pulmonary circulation disease	1151 (23.3)	5934 (17.7)	<0.001
Peripheral vascular disease	808 (16.3)	4711 (14)	<0.001
Hypertension	3309 (66.9)	21 060 (62.7)	<0.001
Paralysis	136 (2.8)	554 (1.6)	<0.001
Other neurological disorders	291 (5.9)	1428 (4.3)	<0.001
Chronic pulmonary disease	1326 (26.8)	7068 (21)	<0.001
Diabetes mellitus	1453 (29.4)	7799 (23.2)	<0.001
Hypothyroidism	645 (13)	3912 (11.6)	0.004
Liver disease	95 (1.9)	497 (1.5)	0.02
Lymphoma	40 (0.8)	190 (0.6)	0.04
Metastatic cancer	17 (0.3)	40 (0.1)	<0.001
Solid tumor without metastasis	77 (1.6)	250 (0.7)	<0.001
Rheumatoid arthritis/collagen vascular disease	196 (4)	957 (2.8)	<0.001
Obesity	813 (16.4)	5100 (15.2)	0.02
Weight loss	332 (6.7)	1258 (3.7)	<0.001
Fluid and electrolyte disorders	1798 (36.4)	9732 (29)	<0.001
Chronic blood loss anemia	119 (2.4)	606 (1.8)	0.004
Deficiency anemias	1350 (27.3)	7239 (21.6)	<0.001
Alcohol abuse	148 (3)	913 (2.7)	0.27
Drug abuse	125 (2.5)	535 (1.6)	<0.001
Psychoses	147 (3)	711 (2.1)	<0.001
Additional comorbidities			
Depression	438 (8.9)	2505 (7.5)	<0.001
Obstructive sleep apnea	442 (8.9)	2816 (8.4)	0.19

Continued

Table 2. Continued

Factor	Readmission, N (%)	No Readmission, N (%)	P Value*
	(N=4943)	(N=33 589)	
Tobacco abuse disorder	1364 (27.6)	9713 (28.9)	0.06
Chronic kidney disease	737 (14.9)	3241 (9.6)	<0.001
End-stage renal disease	293 (5.9)	635 (1.9)	<0.001
Stroke	406 (8.2)	1812 (5.4)	<0.001
Atrial fibrillation	2569 (52.0)	15 369 (45.8)	<0.001
Myocardial infarction	92 (1.9)	446 (1.3)	0.003
Mitral valve disease	1338 (27.1)	8677 (25.8)	0.11
Aortic valve disease	2091 (42.3)	16 139 (48.0)	<0.001
Tricuspid valve disease	89 (1.8)	376 (1.1)	<0.001
Pulmonic valve disease	25 (0.5)	87 (0.3)	0.002
Hospital therapies			
Cardiac rehabilitation	1994 (40.3)	12 699 (37.8)	0.001
Physical therapy	3596 (72.7)	20 669 (61.5)	<0.001
IABP	192 (3.9)	962 (2.9)	<0.001
Immunosuppression	930 (18.8)	4761 (14.2)	<0.001
Packed red blood cells			<0.001
0 units	1202 (24.3)	12 447 (37.1)	
1–2 units	1033 (20.9)	7773 (23.1)	
3–4 units	964 (19.5)	5972 (17.8)	
5 or more units	1744 (35.3)	7397 (22.0)	
ICU days, median (IQR) [†]	4 (2, 7)	2 (1, 5)	<0.001
IMV days, median (IQR) [†]	2 (1, 2)	1 (1, 2)	<0.001
Post-operative infection	914 (18.5)	3239 (9.6)	<0.001

IABP indicates intra aortic balloon pump; ICU, intensive care unit; IMV, invasive mechanical ventilation; IQR, interquartile range; max, maximum; min, minimum.

*Chi-square test.

[†]Kruskal–Wallis test.

point within 3 months of hospital discharge. Given that each Premier hospital uses different patient codes, and not all US hospitals participate in Premier, a readmission to a hospital other than the primary surgical hospital was unidentified. Furthermore, because of the de-identification of patient information and removal of exact readmission dates, it was not possible to compute precise 30- and 90-day readmission. Nevertheless, readmission month and year were known, and therefore approximate 1- and 3-month readmission could be measured. As secondary outcomes, we evaluated readmission within 1 month as well as the primary causes for readmission at 1 and 3 months. We utilized the Agency for Healthcare

Research and Quality's Clinical Classification System (CCS) grouper to identify the cause of readmission on the basis of the patient's principal diagnosis.¹²

Statistical Analysis and Model Development

We computed summary statistics using frequencies and proportions for categorical data, and means, medians, and interquartile ranges (IQRs) for continuous variables. Chi-square and Kruskal–Wallis tests were used to assess the relationship between various patient and health system characteristics with hospital readmission at 1 and 3 months. Before to any modeling, we randomly selected 80% of our hospitals for model derivation. The remaining 20% of hospitals were reserved as a validation cohort after model development.

Because of skewed distributions, we grouped patient age and hospital length of stay in quartiles for modeling and the number of PBRCs per every 2 units transfused. Hospital admission urgency was grouped as emergent versus urgent/elective because we found that each hospital interpreted these terms differently, and furthermore, there were only small differences in readmission rates between the urgent and elective groups.

Using the derivation cohort, we then developed multivariable generalized estimation equation (GEE) models to predict 1- and 3-month readmissions accounting for patient clustering within hospitals. We forced age, sex, and surgical category into the full model to increase face validity and clinical credibility. All other variables were subject to statistical thresholds and modeling fit criteria for inclusion. We used backward selection with $P < 0.05$ as a cutoff to select variables into the model. Discrimination was evaluated using the area under the curve (C-statistic).

Parameter estimates obtained from the derivation cohort were then used to compute individual readmission risk in the validation cohort for 1- and 3-month readmissions. Both cohorts were categorized by decile of risk based on the probability distribution in the derivation cohort, whereas observed readmission rates were compared to model predicted rates by calibration plots. Minimal, maximal, and average discrepancy between expected and observed differences within the deciles of risk in the validation group was calculated as a measure of calibration. We also measured calibration as the absolute difference between smoothed observed outcomes and predicted probabilities and present it as an average of the differences (Harrell's E_{avg}).^{13,14}

Finally, to increase the clinical utility of the model, we reduced the number of variables in an effort to simplify the model to just a handful of variables. To do this, we selected variables with the strongest predictive ability based on descending Wald chi-square values and retaining

the top 5 factors with the highest Wald chi-square values. In addition to clinical reasoning, we also utilized the quasi-likelihood under the independence criterion (QIC; smaller value is better) to guide our decisions and then retested calibration and discrimination in the simplified model. All analyses were performed using SAS (version 9.3; SAS Institute Inc., Cary, NC), STATA (StataCorp 2013; Stata Statistical Software: Release 13; StataCorp LP, College Station, TX), and RMS package of R (R Foundation for Statistical Computing).¹⁵

Results

We identified a total of 38 532 patients who underwent HVS at 219 hospitals during the study period who met inclusion criteria. Overall, the patient population was 56% male, 71% white, patient median age was 67 years, and 55% were Medicare recipients (Table 2). A total of 3125 (7.8%) and 4943 (12.8%) patients were readmitted within 1 and 3 months, respectively. Because of the large sample size, patients with a hospital readmission were statistically different from patients without a hospital readmission in nearly every covariate (Table 2). The most common reasons for hospital readmission were heart failure (12%), cardiac dysrhythmias (11%), and complications of surgical procedures or medical care (11%). Reasons for readmission were generally

similar in the first month, compared to subsequent months (Table 3).

Among the >50 factors evaluated, 20 were included in the final model, with only minor differences depending on whether the patient had been readmitted during the 1- versus 3-month period (Table 4). Notably, patients undergoing either mitral valve surgery or combination valve surgery were at higher risk for readmission when compared to patients undergoing isolated aortic valve surgery. Many patient characteristics were predictive of hospital readmission, including extremes of age, presence of tricuspid valve disease, metastatic cancer, most comorbidities, increased hospital length of stay, and receipt of physical therapy. Important system factors that increased risk for readmission included lower hospital surgical volume and hospital location in the Midwest. The final regression model for 1 month estimated risk of readmission between 1.5% and 47.3% (3.5% and 18% across deciles) with a C-statistic of 0.66 and a Harrell's E_{avg} of 0.2%. Our 3-month final regression model predicted a probability of readmission ranging between 3% and 61% (5% and 29% across deciles) with a C-statistic of 0.67 and a Harrell's E_{avg} of 0.1%.

Model Validation and Simplification

There were some differences between derivation and validation cohort hospitals. The validation cohort generally had a

Table 3. Primary Reasons for Hospital Readmission After Heart Valve Surgery by Readmission Time Frame

CCS Grouping	Month 1	CCS Grouping	Months 2–3
No. of Patients Readmitted	N=3125 (%)	No. of Patients Readmitted	N=1818 (%)
Congestive heart failure; nonhypertensive	365 (11.7)	Congestive heart failure; nonhypertensive	209 (11.5)
Cardiac dysrhythmias	338 (10.8)	Cardiac dysrhythmias	162 (8.9)
Complications of surgical procedures or medical care	335 (10.7)	Complications of surgical procedures or medical care	118 (6.5)
Complication of device; implant or graft	165 (5.3)	Complication of device; implant or graft	114 (6.3)
Peri-, endo-, and myocarditis; cardiomyopathy*	156 (5.0)	Septicemia (except in labor)	90 (4.5)
Pleurisy; pneumothorax; pulmonary collapse	124 (4.0)	Acute cerebrovascular disease	48 (2.6)
Septicemia (except in labor)	119 (3.8)	Pleurisy; pneumothorax; pulmonary collapse	45 (2.5)
Acute cerebrovascular disease	81 (2.6)	Peri-, endo-, and myocarditis; cardiomyopathy*	45 (2.5)
Pneumonia*	74 (2.4)	Nonspecific chest pain	40 (2.2)
Respiratory failure; insufficiency; arrest (adult)	56 (1.8)	Pneumonia*	37 (2.0)
Gastrointestinal hemorrhage	49 (1.6)	Respiratory failure; insufficiency; arrest (adult)	30 (1.7)
Nonspecific chest pain	48 (1.5)	Gastrointestinal hemorrhage	28 (1.5)
Fluid and electrolyte disorders	46 (1.5)	Urinary tract infections	28 (1.5)
Acute and unspecified renal failure	44 (1.4)	Coronary atherosclerosis and other heart disease	27 (1.5)
Residual codes; unclassified	43 (1.4)	Acute and unspecified renal failure	27 (1.5)

CCS indicates clinical classification system.

*Except that caused by tuberculosis or sexually transmitted disease.

Table 4. Final Predictive Model for 1- and 3-Month Readmission After Heart Valve Surgery

Parameter	1 Month	3 Month	Wald χ^2
	OR (95% CI)	OR (95% CI)	
Age, yr			15.3
18–54	1.24 (1.09–1.42)	1.22 (1.09–1.37)	
55–64	Ref	Ref	
65–74	1.06 (0.93–1.20)	1.10 (0.99–1.22)	
75+	1.16 (1.02–1.32)	1.19 (1.07–1.32)	
Sex (male)	0.93 (0.85–1.01)	0.92 (0.86–0.99)	4.8
Procedure			18.1
Aortic	Ref	Ref	
Mitral	1.23 (1.12–1.36)	1.18 (1.09–1.28)	
Combination	1.38 (1.18–1.60)	1.26 (1.11–1.44)	
Tricuspid valve disease	1.65 (1.21–2.27)	1.52 (1.15–2.01)	6.1
Surgical* volume (per 50 cases)	0.95 (0.94–0.97)	0.95 (0.93–0.98)	6.4
Length of stay (min–max, days)			39.3
Quartile 1 (1–5)	Ref	Ref	
Quartile 2 (6–7)	1.16 (1.00–1.35)	1.24 (1.10–1.40)	
Quartile 3 (8–12)	1.35 (1.16–1.56)	1.44 (1.27–1.63)	
Quartile 4 (13+)	1.78 (1.51–2.09)	1.80 (1.57–2.07)	
Admission type			26.1
Emergency	1.21 (1.08–1.36)	1.37 (1.25–1.51)	
Urgent/elective	Ref	Ref	
Comorbidities			
Congestive heart failure	†	1.17 (1.08–1.26)	11.9
Peripheral vascular disease	1.19 (1.06–1.33)	1.14 (1.04–1.26)	6.8
Hypertension	1.14 (1.04–1.26)	1.14 (1.06–1.23)	11.3
Chronic lung disease	1.16 (1.05–1.27)	1.13 (1.04–1.23)	6.4
Diabetes mellitus	1.23 (1.12–1.35)	1.18 (1.09–1.28)	13.4
Metastatic cancer	3.25 (1.62–6.52)	2.43 (1.25–4.72)	3.8
Solid tumor without metastasis	1.87 (1.29–2.70)	1.93 (1.41–2.63)	10.7
Arthritis	†	1.27 (1.06–1.53)	4.2
End-stage renal disease	1.84 (1.50–2.26)	2.03 (1.70–2.43)	20.5
Chronic kidney disease	†	1.19 (1.07–1.32)	8.0
Atrial fibrillation	1.11 (1.01–1.21)	1.08 (1.00–1.17)	4.5

Continued

Table 4. Continued

Parameter	1 Month	3 Month	Wald χ^2
	OR (95% CI)	OR (95% CI)	
Alcohol abuse	0.71 (0.53–0.94)*	†	
Postoperative infection	†	1.21 (1.09–1.34)	10.6
Use of physical therapy	1.23 (1.10–1.37)	1.19 (1.09–1.31)	9.3
Packed red blood cells, units			20.0
0	Ref	Ref	
1–2	1.22 (1.07–1.39)	1.10 (0.99–1.22)	
3–4	1.31 (1.14–1.50)	1.17 (1.04–1.31)	
5+	1.46 (1.27–1.67)	1.32 (1.18–1.48)	
Hospital region			12.6
Northeast	†	1.09 (0.93–1.29)	
Midwest	†	1.29 (1.13–1.48)	
West	†	0.96 (0.84–1.09)	
South	†	Ref	

max indicates maximum; min, minimum; OR, odds ratio; Ref, reference.

*Hospital surgical volume includes all coronary artery bypass graft and heart valve surgeries performed at that hospital annually.

†These factors were not statistically significant in the 1- or 3-month models and were excluded.

greater proportion of large, teaching, and northeastern hospitals, suggesting that this cohort was different enough to be useful for validation (Table 5). When applied to the validation cohort, our final 3-month model predicted hospital readmission with a C-statistic of 0.67, which was similar to model performance in the derivation cohort. In calibration plots, the absolute difference in predicted risk and observed readmission in the validation cohort averaged 1.9% (range, 1–4) in each decile of predicted risk with a Harrell's E of 1.6%, suggesting good calibration. Notably, the model had better discrimination at higher levels of risk than it did among patients with an estimated readmission risk of <10% (Figure 1).

For the simplified model, we retained the 5 strongest predictors (highest Wald chi-square in Table 4) of 3-month readmission: transfused units of packed Red blood cells, presence of End stage renal disease, type of Valve surgery, Emergency hospital admission, and hospital Length of stay (REVEaL). Though there was some loss of discrimination (C-statistic of 0.65), overall, the model retained similar properties and calibration (Figure 2). The addition of the next most important variables (age and diabetes mellitus) did not significantly increase discrimination (C-statistic, 0.65) and resulted in only a minimally improved model fit (QIC 21 794

Table 5. Hospital Characteristics by Derivation and Validation Cohort

Hospital Characteristics	Development Cohort	Validation Cohort	P Value
No. of hospitals (%)	175 (80)	43 (20)	
Bed size (%)			0.24
<200 beds	16 (9.1)	4 (9.3)	
201–400 beds	85 (48.6)	15 (34.9)	
>401 beds	74 (42.3)	24 (55.8)	
Urban location (%)	154 (88.0)	40 (93.0)	0.34
Teaching hospital (%)	65 (37.1)	20 (46.5)	0.26
Region (%)			0.03
Northeast	18 (10.3)	11 (25.6)	
Midwest	43 (24.6)	11 (25.6)	
West	45 (25.7)	5 (11.6)	
South	69 (39.4)	16 (37.2)	

vs 21 827 for the 5-variable model); inasmuch, these variables were excluded. The final weighting of the variables is shown in Table 6, and a nomogram is shown in Figure 3. Based upon approximate tertiles of estimated risk, cutoffs for low (score <53), medium (score between 53 and 105), and high risk (score >105) were found to be associated with readmission rates of <10%, between 10% and 15%, and >15%, respectively.

Discussion

Using a large multihospital database, we developed and validated a predictive model intended to identify patients at increased risk for hospital readmission, at the time of hospital discharge post-HVS. Because of the size of our database and the large network of hospitals that contributed data to this study, our model is statistically robust and likely generalizable. Furthermore, we found that, with comparable discrimination and calibration to existing CABG models used for hospital profiling,³ the risk for hospital readmission could be reasonably predicted across a broad range of risk. In addition to a full 20-variable model, we also developed a simplified model using readily available clinical data that had nearly equivalent performance metrics and should be clinically applicable. As a result, we believe that this model has significant potential for routine clinical use by clinicians seeking to target transitional care interventions for high-risk patients.

To our knowledge, this is the first time a readmission model has been developed specifically for patients with HVS in the United States and the first time 3-month readmission has been used as the primary outcome. Therefore, our model

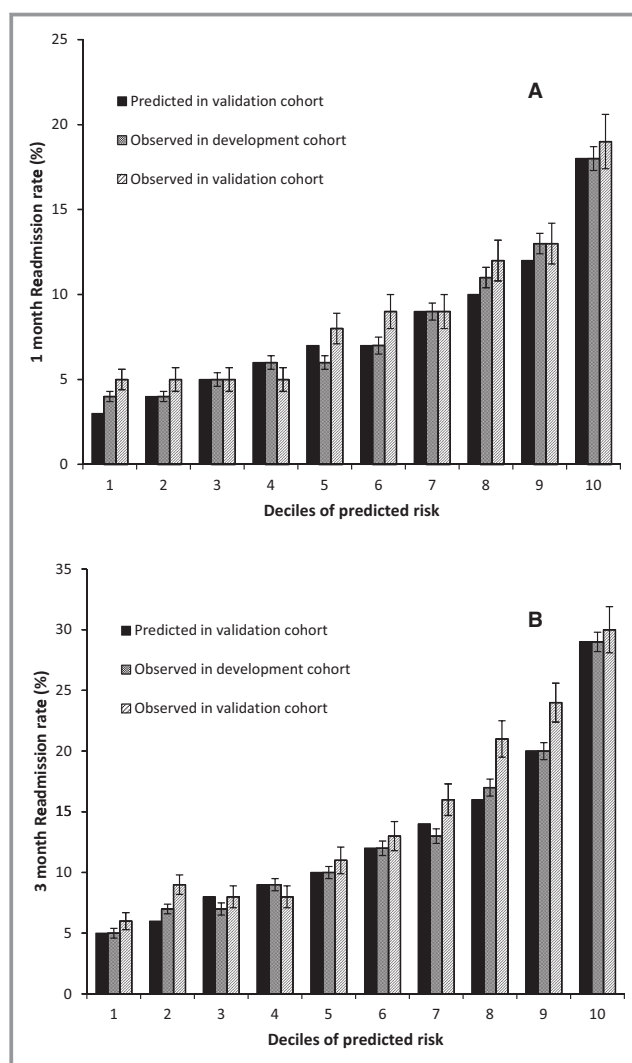


Figure 1. Observed versus model predicted readmission risk in development and validation cohorts at 1 (A) and 3 months (B).

should be particularly useful to hospitals participating in 90-day bundled payments through Medicare for patients with HVS, but it will also have applicability to programs working to reduce 30-day readmission.

A key finding of our predictive model is that patients with either isolated mitral valve or combination valve procedures were at $\approx 25\%$ higher risk of hospital readmission, when compared to patients who underwent an isolated aortic valve procedure. This finding is consistent with existing literature^{7,16} and is likely attributed to the increased surgical complexity in performing mitral valve surgery. It is also consistent with the known significant preoperative deconditioning and heart failure¹⁷ associated with mitral valve disease.

Our study also confirms a number of shared risk factors for readmission among patients with HVS that have been previously described among patients with CABG. Specifically,

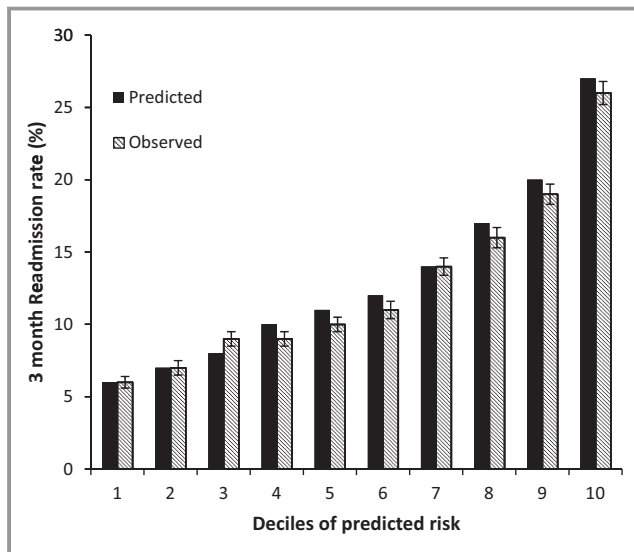


Figure 2. Calibration plot for derivation cohort at 3 months using a 5-parameter model.

we found that a longer hospital stay, emergency hospital admissions, presence of comorbid tricuspid disease, increased comorbidity burden, postoperative complications,

Table 6. Final Weights in 5-Parameter Nomogram

Parameter	Nomogram Points
Length of stay (min–max, days)	
Quartile 1 (1–5)	0
Quartile 2 (6–7)	35
Quartile 3 (8–12)	60
Quartile 4 (13+)	100
Admission type	
Emergency/trauma	32
Nonemergency	0
End-stage renal disease	
Yes	78
No	0
Packed red blood cells, units	
0	0
1–2	17
3–4	27
5+	42
Surgical procedure type	
Aortic	0
Mitral	16
Combination	21

max indicates maximum; min, minimum.

and lower hospital surgical volume were risk factors for patients with HVS just as they are for patients with CABG.^{3–5,16} Additionally, the causes of readmission at both the 1- and 3-month periods in the study are similar to that for patients with CABG.⁴ Given that both surgeries share multiple operative and disease characteristics, it is not surprising that these 2 surgical groups would share similar risk factors and readmission diagnoses.

Although use of physical therapy and blood transfusion were associated with increased risk of readmission, we do not believe that these interventions are necessarily harmful, but instead reflect a greater severity among treated patients that were not accounted for by other model covariates. Nevertheless, a recent study found that a hemoglobin level <8.0 mg/dL did not increase risk for readmission, but the use of transfusion did.¹⁸ Additionally, 2 other studies suggest that although postoperative anemia is a risk marker for adverse outcomes, there is no benefit, and there is probably harm, in transfusing asymptomatic patients with a hemoglobin level >8.0 mg/dL.^{19,20} Moreover, recent quality improvement efforts to minimize blood transfusion have led to improved outcomes in patients with cardiac surgery.²¹ Therefore, though blood transfusion is certainly a marker for increased readmission risk, it may also be true that pursuing a restrictive blood transfusion strategy could reduce readmission risk.

Importantly, we developed our models with the intention of giving clinical providers a tool for risk-stratifying patients at the time of hospital discharge and therefore included factors such as length of stay and blood transfusions. Accordingly, our models are not suitable for creating risk-standardized readmission rates or for hospital profiling because it includes hospital-level characteristics and includes events that occurred after admission, which are influenced by hospital practice.

Appropriate risk stratification with tools such as our readmission risk model can help tailor interventions to those most likely to benefit. Although interventions such as follow-up clinic appointments made before discharge²² and outpatient cardiac rehabilitation²³ have been associated with reduced readmission rates, there are few reasons why these interventions should not be offered to all patients, regardless of risk. On the other hand, interventions that are expensive or require a significant time investment, such as inpatient rehabilitation, nursing home placement, or intensive case management, are neither appropriate nor necessary for all patients. In such cases, risk stratification tools such as our readmission model can help direct the more costly interventions to patients who are more likely to benefit from them.

The limitations of our statistical model are several-fold. First, because the Premier data set does not capture readmissions to nonindex hospitals, our readmission rates

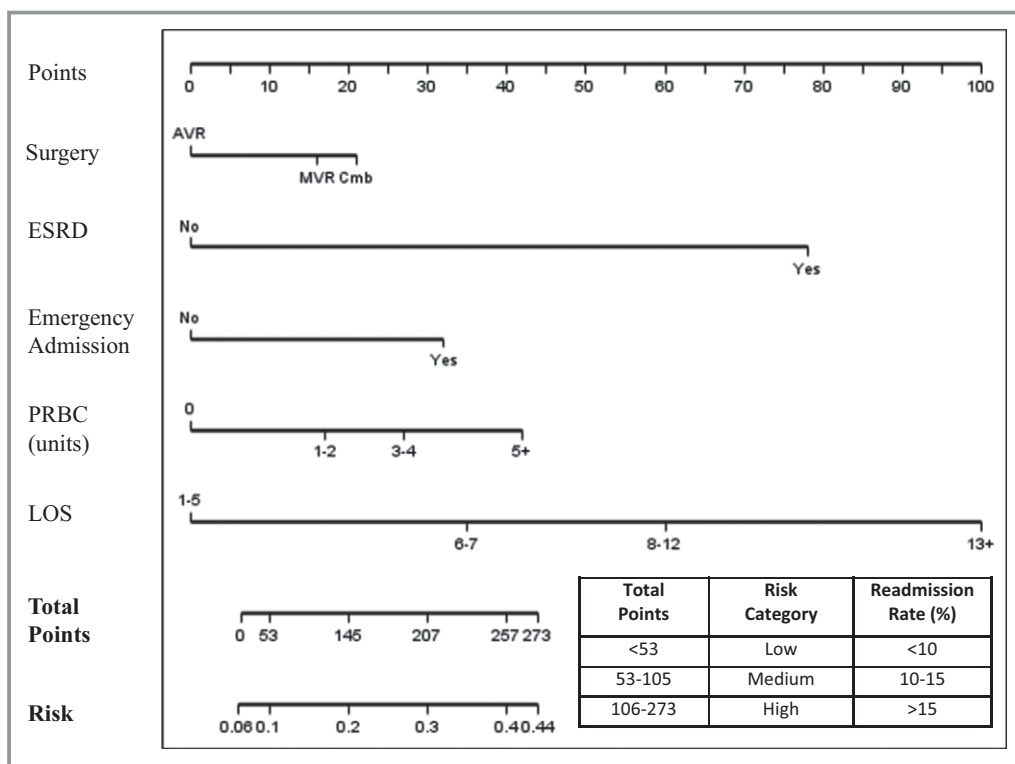


Figure 3. Five variable nomogram for predicting 3-month hospital readmission after heart valve surgery. Example: If a patient underwent AVR during an elective admission, did not have ESRD, received 4 units of PRBCs, and was hospitalized for 10 days, this person’s points for each category would be 0, 0, 0, 27, and 60, respectively, for a total of 87 points. This would give the patient a medium risk of 3-month readmission with an estimated rate of around 13%. AVR indicates aortic valve replacement; ESRD, end-stage renal disease; LOS, length of stay; MVR, mitral valve repair/replacement; PRBC, packed red blood cells.

are probably underestimated. Indeed, 30-day readmission after mitral valve surgery and aortic valve surgery among older Medicare adults typically ranges between 15% and 20%,^{9,24} and we observed 1- and 3-month readmission rates of only 7.8% and 12.8%, respectively, in our population. Consequently, although our patient population was younger than these Medicare populations, it is likely that our model underestimates the total risk of readmission when all hospitals are considered. Additionally, factors that predict index-hospital readmission could also differ from factors that predict total readmission. Nevertheless, because our model contains important in-hospital treatment factors that are unavailable in Medicare data, we believe our model is clinically useful to risk stratify patients into low versus increased risk and should be well calibrated to predict readmission rates to index hospitals where the surgery was performed. In the future, external validation and recalibration can potentially provide more-accurate probability estimates. Second, the exact etiology of the valve disease, the reason for the surgery, or specific surgical techniques were unavailable, which limits our ability to explore patient subgroups and various surgical techniques for their impact on hospital readmission. Last, we were unable to compute exact 30- and 90-day readmission

rates. However, if the focus is improving quality and identifying potential strategies to prevent readmission rather than meet a specific readmission performance measure, our model adds to the literature in many ways.

Conclusions

In conclusion, we developed and validated a predictive model for 1- and 3-month hospital readmission for patients undergoing HVS and created a simple 5-variable model that could be used at the bedside. Our results highlight several important risk factors in this population, some of which may be modifiable. We anticipate that our results will help hospitals and clinicians identify patients who are at increased risk for hospital readmission after undergoing HVS and who are most likely to benefit from improved postdischarge care and follow-up.

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Disclosures

None.

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