Heart, Lung and Circulation (2019) **28**, 1896–1903
1443-9506/04/$36.00
https://doi.org/10.1016/j.hlc.2018.11.007

ORIGINAL ARTICLE

Risk Calculator to Predict 30-Day Readmission After Coronary Artery Bypass: A Strategic Decision Support Tool

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Received 14 June 2018; received in revised form 11 October 2018; accepted 13 November 2018; online published-ahead-of-print 29 November 2018

Background Re-admission is an important source of patient dissatisfaction and increased hospital costs. A simple calculator to determine the probability of re-admission may help guide patient dismissal planning.

Methods Using the national readmissions database (NRD), we identified admissions for isolated primary coronary artery bypass (CABG) and stratified them according to 30-day readmission. Including pre, intra and post-operative variables, we prepared a logistic regression model to determine the probability for re-admission. The model was tested for reliability with boot-strapping and 10-fold cross-validation.

Results From 135,699 procedures, 19,355 were readmitted at least once within 30 days of dismissal. Patients who were readmitted were older (67 $\pm$ 10 vs 65 $\pm$ 10 years, p <0.01), females (32% vs 24%; p < 0.01) and had a higher Elixhauser comorbidity score (1.5 $\pm$ 1.4 vs 1.1 $\pm$ 1.2; p < 0.01). Our final model (c- statistic = 0.65) consisted of 16 pre and three postoperative factors. End-stage renal disease (OR 1.79 [1.57–2.04]) and length of stay > 9 days (OR 1.60 [1.52–1.68]) were most prominent indicators for readmission. Compared to Medicaid beneficiaries, those with private insurance (OR 0.62[0.57–0.68]) and Medicare (OR 0.85[0.79–0.92]) coverage were less likely to be readmitted.

Conclusions Our simple 30-days CABG readmission calculator can be used as a strategic tool to help reduce readmissions after coronary artery bypass surgery.

Keywords Readmission • Risk calculator • Coronary artery bypass grafting

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Introduction

Coronary artery bypass grafting (CABG) is one of the most commonly performed major surgical operations in the world with about 400,000 procedures performed annually in the US alone. CABG results are carefully scrutinised; hospital rankings and reputations are partly dependent on that. Risk models for a variety of postoperative outcomes are available through the Society of Thoracic Surgeons (STS) database for clinical practice benchmarking. These outcomes include hospital mortality, morbidity and length of stays. In 2012, the Centers for Medicare and Medicaid Services (CMS) introduced the Hospital Readmission Reduction Program (HRRP) [1], which enforced financial penalties on hospitals with high 30-day readmission rates. Starting in January 2017, CMS has included CABG in this program, making it imperative for hospitals to rein in their CABG readmissions rates. Readmission is also an important factor that leads to increased patient dissatisfaction and procedural cost [2]. Therefore, using the national readmissions database (NRD), we sought to develop a risk-score which could help surgeons in identifying patients at high-risk of readmission after discharge, so that necessary steps can be taken to reduce their chances of readmission.

Methods

The NRD is a unique and powerful database designed to support various types of analyses of national readmission rates for all payers and the uninsured. The NRD contains discharge data from 27 geographically dispersed states, accounting for 57.8% of the total US resident population and 56.6% of all US hospitalisations, amounting to roughly 36 million discharges nationally [4]. Developed through a Federal-State-Industry partnership sponsored by the Agency for Healthcare Research and Quality, Healthcare Cost and Utilization Project (HCUP) data inform decision making at the national, state, and community levels. The methodology for extraction of these cases was followed as recommended by the Agency for Healthcare Quality [5]. We analysed the NRD database from 1 January 2014 to 30 November 2014 and identified adult (>18 years) patients with 30-day readmission after coronary revascularisation (*ICD 9 codes 36.10, 36.11, 36.12, 36.13, 36.14, 36.15, 36.16*) as their prior index procedure [3]. Admissions that resulted in in-hospital mortality were naturally excluded from analysis. When the same individual had more than one readmission, only the first event was included. In an effort to obtain patients with isolated primary coronary artery bypass grafting, we excluded those who underwent concomitant valve procedures during the same admission (*35.11–35.14, 35.21–35.28*), as well as patients having a prior CABG procedure earlier (*V45.81*) [3]. Comorbidities for each admission were obtained using relevant ICD-9 codes from the columns of primary and secondary diagnoses. The Elixhauser scoring system was also implemented [6]. We have provided a detailed list of ICD-9-CM codes in the online supplement.

Statistical analysis was performed in R 3.4.3 [7]. Categorical data are presented as counts (percentages) while

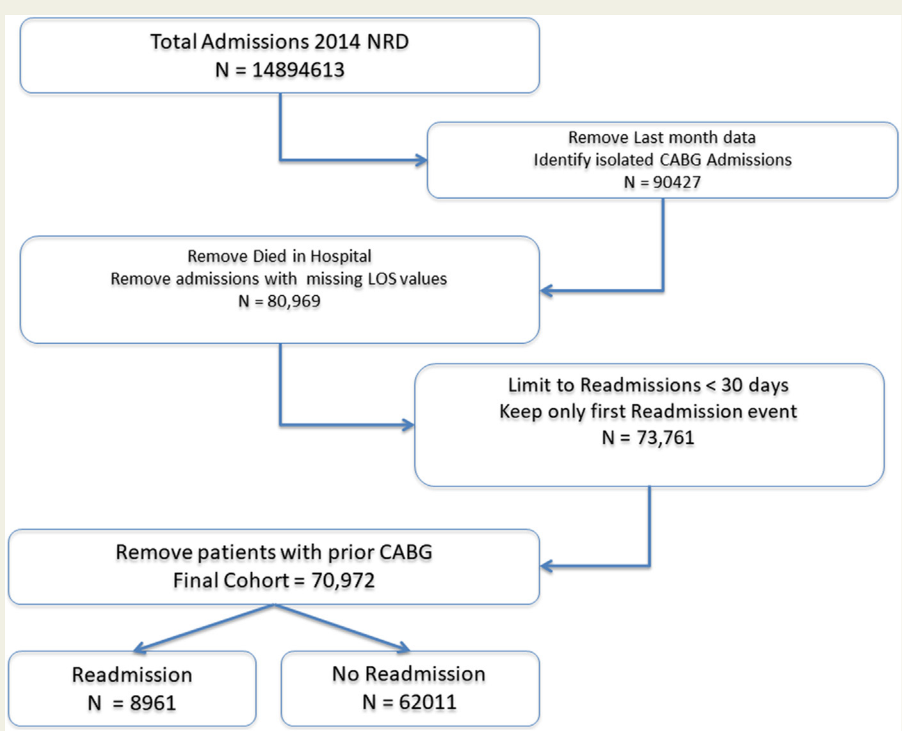

Figure 1 This flowchart depicts the selection process for our cohort study.

continuous data are presented as median (inter-quartile range). We stratified our study cohort into those who did and did not experience 30-day readmission. Categorical data is compared with the Chi square test while continuous data was analysed with the Wilcoxon rank-sum test or two-tailed 't' test as per normality. National estimates are provided with the 'survey' package with certainty correction for single PSU units [8]. HCUP recommends that using a hierarchical regression model to account for patient clustering within hospitals [9,10] Thus, our final model was also developed with hierarchical regression using the hospital identifier as the random effects term. The mixed effects model demonstrates the contribution of clustering to the model (random effects variance = 0.0004, SD = 0.02) was

Table 1 **This table presents the baseline demographics for our study cohort.**

Variables Studied	No Readmission N = 135,699	Readmission N = 19,355	P-value
Age	65.2 (10.4)	67 (10.7)	<0.001
Female	32,940 (24)	6,169 (32)	<0.001
Old age (>80 years)	9,263 (7)	2,065 (10)	<0.001
Prior myocardial infarction	20,133 (14)	3,078 (16)	0.01
Prior stroke	7,835 (6)	1,435 (8)	<0.001
Prior PPM implant	1,818 (1)	457 (2)	<0.001
Prior ICD implant	962 (<1)	173 (<1)	0.09
Prior percutaneous intervention	21,545 (16)	3,082 (16)	0.92
Concomitant mitral valve disease	1,405 (1)	245 (1)	0.12
Congestive heart failure	25,781 (19)	5,767 (30)	<0.001
Atrial fibrillation	25,552 (18)	4,396 (22)	<0.001
End-stage renal disease	2,151 (1)	675 (3)	<0.001
Renal disease	18,428 (13)	4,148 (21)	<0.001
Carotid artery stenosis	8,350 (6)	1,434 (7)	<0.001
COPD	28,355 (21)	5,335 (27)	<0.001
Peripheral vascular disease	20,497 (15)	3,884 (20)	<0.001
Liver disease	2,357 (1)	510 (2)	<0.001
Diabetes mellitus	59,518 (43)	9,742 (50)	<0.001
Obesity	33,706 (25)	5,255 (27)	<0.001
Cancer	2,188 (1)	388 (2)	0.02
Weight loss	3,464 (2)	1,013 (5)	<0.001
Anaemia	22,890 (17)	4,456 (23)	<0.001
Payer status: Medicaid	9,629 (7)	1,763 (9)	<0.001
Medicare	73,195 (54)	12,297 (64)	
Others	8,703 (7)	1,135 (6)	
Private insurance	43,897 (32)	4,122 (21)	
Hospital size: Small	11,990 (9)	1,559 (9)	0.05
Medium	31,673 (23)	4,335 (22)	
Large	92,034 (68)	13,460 (69)	
Hospital Location: Large metropolitan area	67,071 (49)	10,121 (52)	0.01
Rural area	2,918 (3)	401 (3)	
Small metropolitan area	65,708 (48)	8,831 (45)	
Teaching hospital	107,470 (79)	15,295 (79)	0.75
Acute stroke	1,398 (1)	261 (1.3)	0.01
Need for mechanical circulatory support	115 (<1)	22 (<1)	0.29
Cardiopulmonary resuscitation	2,009 (1)	449 (2)	<0.001
Acute renal failure	10,816 (8)	2,489 (13)	<0.001
Bleed	53,598 (39)	8,268 (42)	<0.001
Cardiac tamponade	563 (<1)	129 (<1)	0.04
Infection	792 (<1)	199 (1)	<0.001
Length of stay (days)	9.1 (7)	12.5 (9)	<0.001
Long stay (>9 days)	44,057 (32)	9,857 (51)	<0.001

Abbreviations: PPM, permanent pacemaker; ICD, implantable cardioverter-defibrillator; COPD, chronic obstructive pulmonary disease.

negligible. Given the non-significant contribution of the random effects model, we eventually performed a fixed-effects logistic regression with the 'lrm' package in R [11] to identify pre- and post-procedural factors that impact readmission. Variables that did not contribute to the model were the excluded. The CMS has implemented this strategy in their risk calculators [12]. The median length of stay in our data was 8 days. We therefore stratified this variable into *prolonged length of stay (PLOS)* (yes > 9 days, no ≤ 9 days). Patient age was stratified into variable *old age* (yes > 80 - years; no ≤ 80 years). All results are presented at the 95% confidence level.

Model calibration with bootstrapping (1,000 replications) demonstrates that our ruler is accurate for predicting 30-day readmission risk up to 30% (mean absolute error = 0.002).

Missing data were very minimal in the NRD database. Payer status had 159/70,792(0.2%) missing data; all other variables included in the logistic regression were complete. Hence, only complete cases were included in the regression models created. The study was conducted according to the recommended guidelines [13].

Results

Our analysis of the 2014 NRD database identified 70,972 unweighted admissions for primary isolated coronary artery bypass grafting. Of these, 8,961 were readmitted at least once with 30 days of dismissal. Figure 1 outlines our methods for isolating the study cohort. Nationally, from an estimated 135,699 surgical coronary revascularisation procedures, 19,355 (12.5%) had at least one readmission event during 30 days. Patients who were readmitted were older (mean 67 years vs 65 years; $p < 0.01$), more likely women (32% vs. 24%; $p < 0.001$) and had higher Elixhauser morbidity scores (1.5 ± 1.4 vs. 1.1 ± 1.2; $p < 0.01$). Table 1 presents the baseline demographics of patients included in our study.

Our initial kitchen-sink model incorporated 37 pre- and post-procedural variables. After elimination, we developed our final calculator consisting of 16 preoperative and three postoperative factors. Figure 2 provides OR estimates for the predictors included in our final model. The c-statistic for the model is 0.65. As depicted, the most important variables contributing to the model are end-stage renal disease (OR 1.79 [1.57–2.04]) and prolonged length of stay (OR 1.60 [1.52–1.68]). Apart from that, atrial fibrillation (OR 1.22 [1.15–1.29]), female gender (OR 1.28[1.21–1.34]) and weight loss (OR 1.37[1.22–1.52]) remain important variables. Compared to Medicaid beneficiaries, private insurance (OR 1.62 [1.57–0.67]) patients had the least likelihood for readmission. From the seven postoperative factors (acute renal failure, pericardial effusion/cardiac tamponade, major bleeding, infection, acute stroke) and PLOS, important contributorsto our final score were acute renal failure (OR 1.19 [1.11–1.28]), infection (OR 1.27[1.01–1.61]), and PLOS (OR 1.60[1.52–1.68]).

Our ruler (Figure 3) can be easily implemented to calculate the predicted probability of a patient to have a 30-day readmission after CABG. Each variable in the calculator is provided with a score obtained from the raw estimates/standard error derived from the logistic regression model. The probability of readmission is obtained from the probability scale by matching the total points obtained by that patient. For example (Figure 4), a 68-year-old female Medicare patient with renal dysfunction who develops acute renal failure after surgery and went home after 7 days in the hospital would have a total score of 170 (*female (40) + renal dysfunction (40) + Medicare (60) + acute renal failure (30) = 170)*. This would correspond to an approximately 13–14% probability of readmission.

Discussion

Principal Findings

Using the 2014 National Readmissions Database, we analysed admissions for primary CABG and identified those with at least one unanticipated re-admission within 30 days of dismissal. We estimated a national readmission rate of around 12%. Patients needing readmission were older, females and had a higher Elixhauser comorbidity score. We devised a simple 30-day CABG readmission prediction model consisting of 16 pre and three postoperative factors. End-stage renal disease and length of stay (>9 days) were most prominent indicators for readmission. Compared to Medicaid beneficiaries, those with private insurance and Medicare were less likely to get readmitted.

Findings in Context

Re-admissions following hospital discharge not only influence patient satisfaction but also increase overall health care costs [14]. To rein in the readmission rates, the Center for Medicare and Medicaid Services (CMS) introduced the Hospitals Readmissions Reduction Program (HRRP). CMS calculates risk-adjusted expected and predicted readmission ratios for the medical centre. Hospitals with O/E ratio > 1 are financially penalised. Initially limited to medical conditions, this readmissions reduction program was expanded in 2017 to include CABG. This has resulted in studies that aim to identify factors associated with a higher risk of readmissions. Independent researchers have prepared risk models to help determine the probability of readmissions after CABG [15–18].

Shahian et al. [16] linked the Society of Thoracic Surgeons data with Medicare readmissions claims to devise a 30-day readmission model. They found dialysis, increased creatinine levels, severe chronic lung disease, preoperative atrial fibrillation, insulin dependent diabetes mellitus, female gender, immunosuppressive therapy, recent myocardial infarction, low body surface area in men and obesity in women, as factors associated with higher likelihood of 30-day readmission after CABG. The c-statistic of their model was 0.65 and the readmission rate in their study varied from 12.6% to 23.6% across 846 US hospitals. Three (3) features differentiate our model from theirs. First, their

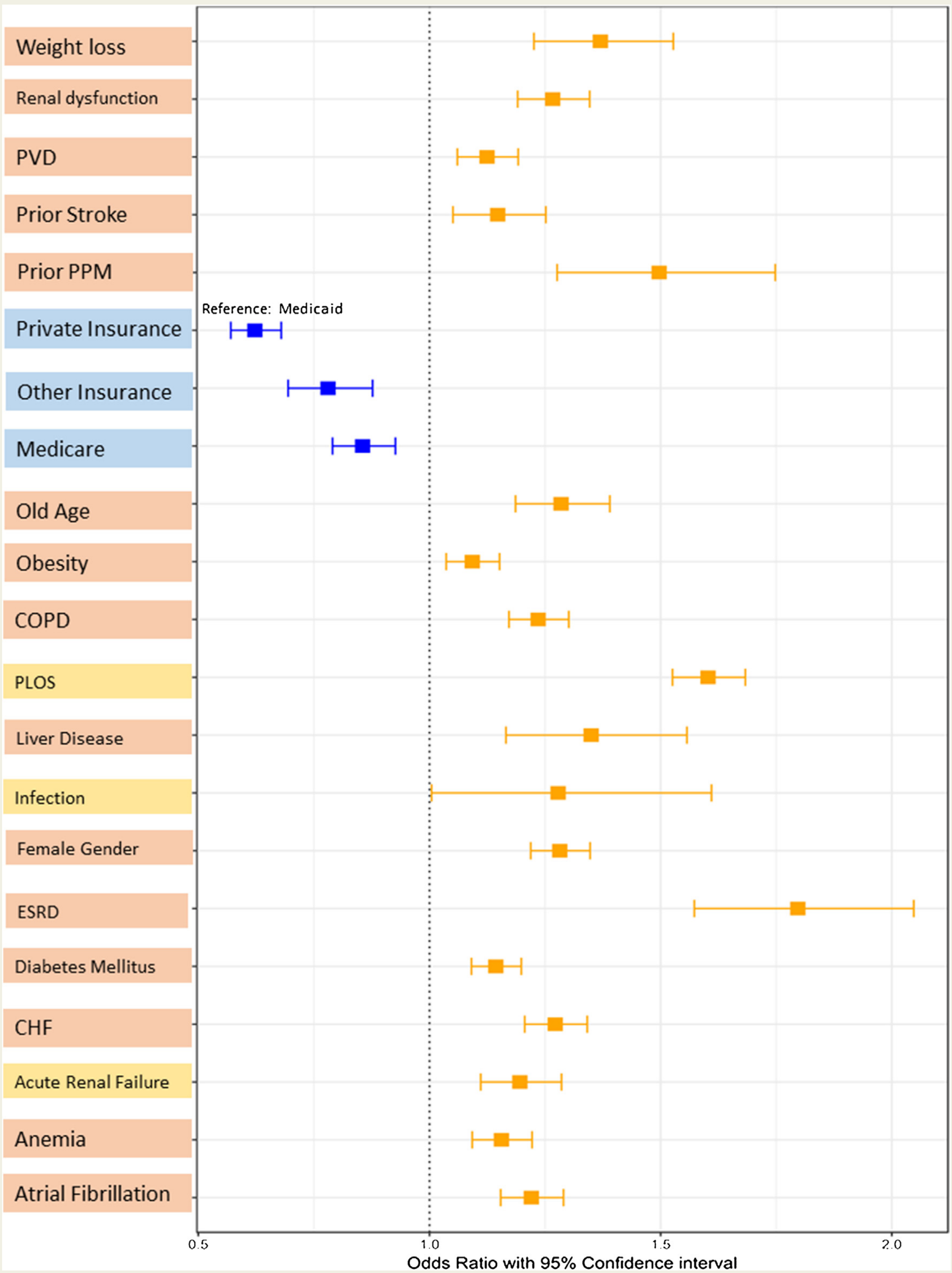

Figure 2 This forest plot presents the Odds Ratio with 95% confidence interval for our logistic regression model to determine significant predictors of 30-day readmission after coronary artery bypass surgery.
Abbreviations: PVD, peripheral vascular disease; PPM, permanent pacemaker implant; COPD, Chronic obstructive pulmonary disease; PLOS, prolonged length of stay; ESRD, end stage renal disease; CHF, congestive heart failure; ESRD, end stage renal disease; RD, renal dysfunction; PVD, peripheral vascular disease; COPD, chronic obstructive pulmonary disease; LOS, length of stay.

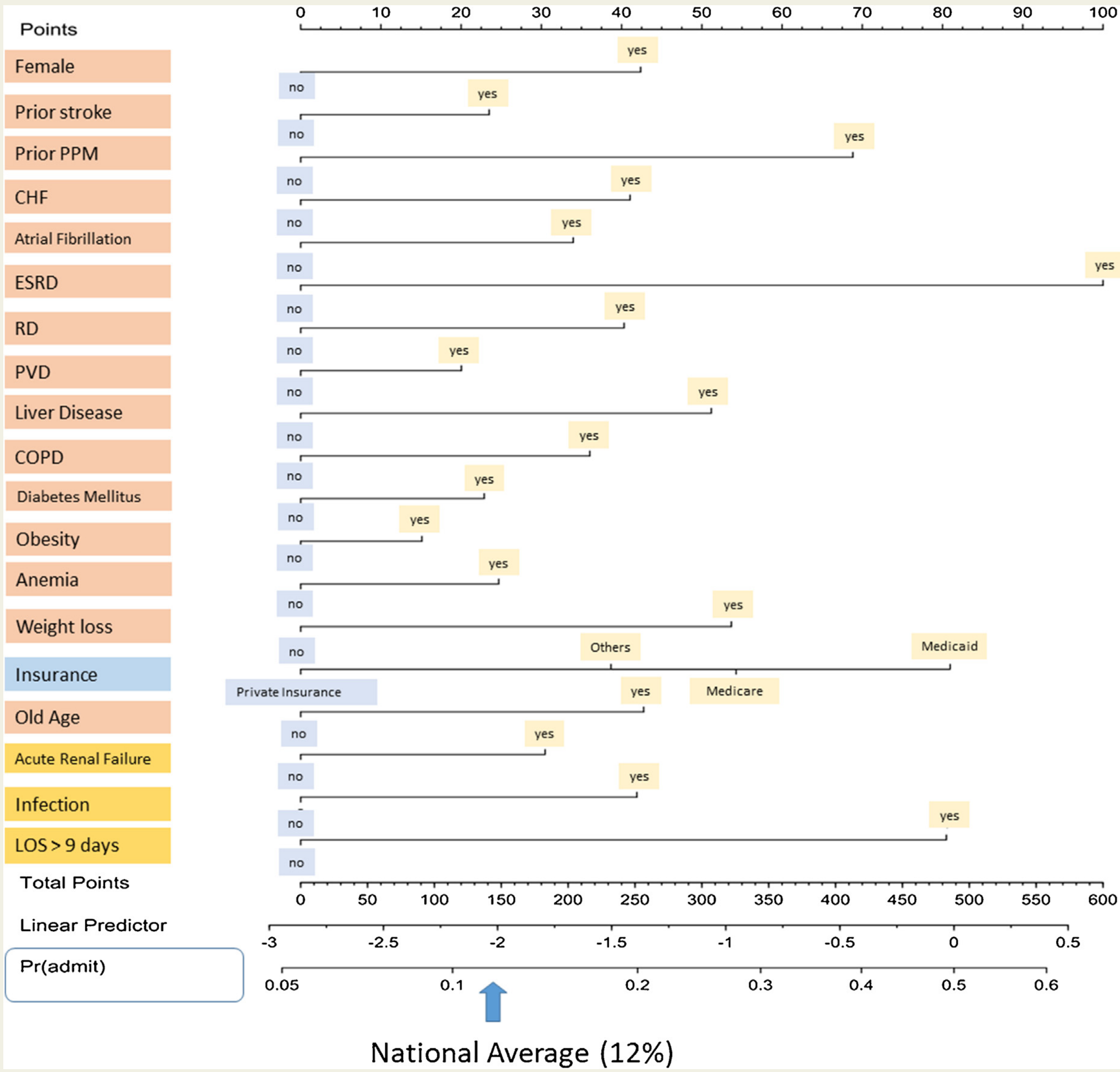

Figure 3 The figure presents our 30-day Readmissions Calculator. Each variable is allotted points according to the top-most scale. From the total points obtained, we can determine probability of readmissions using the *Pr (admit)* line at the bottom. Abbreviations: CHF, congestive heart failure; ESRD, end stage renal disease; RD, renal dysfunction; PVD, peripheral vascular disease; COPD, chronic obstructive pulmonary disease; LOS, length of stay.

model is directly applicable to patients 65 years of age as we have included all adult patients. While their model is based on Medicare patients, we have been able to include all payers; in fact, we demonstrate significant differences in readmission according to payer type. Our model is based on contemporary data; studies have demonstrated changes in patient risk profiles and our model accounts for this change [19].

Zywot et al. [15] devised 100-point readmission risk score based only on preoperative factors using the State Inpatient Database (SID) for New York, California, Washington and Florida. While their model has a higher c-statistic, we feel that our model is more intuitive to use in regular clinical practice. They have presented a 100-point risk scale without specifically providing data of how to convert this into a clear probability for the individual patient. Our ruler gives a simple comparison of total score and probability.

The Center for Medicare Services has presented a model with a c-statistic of 0.62 when applied to the development model and 0.63 when applied to the validation samples. While their model is limited to preoperative data, our ruler also takes into account important postoperative events that influence readmission. Again, the important contribution of payer coverage is not addressed in their analysis.

Decision Support Tool

The primary advantage of our calculator is that it can be easily incorporated into the electronic medical environment. The algorithm will capture comorbidities from the patient records and provide clinicians with a probability of

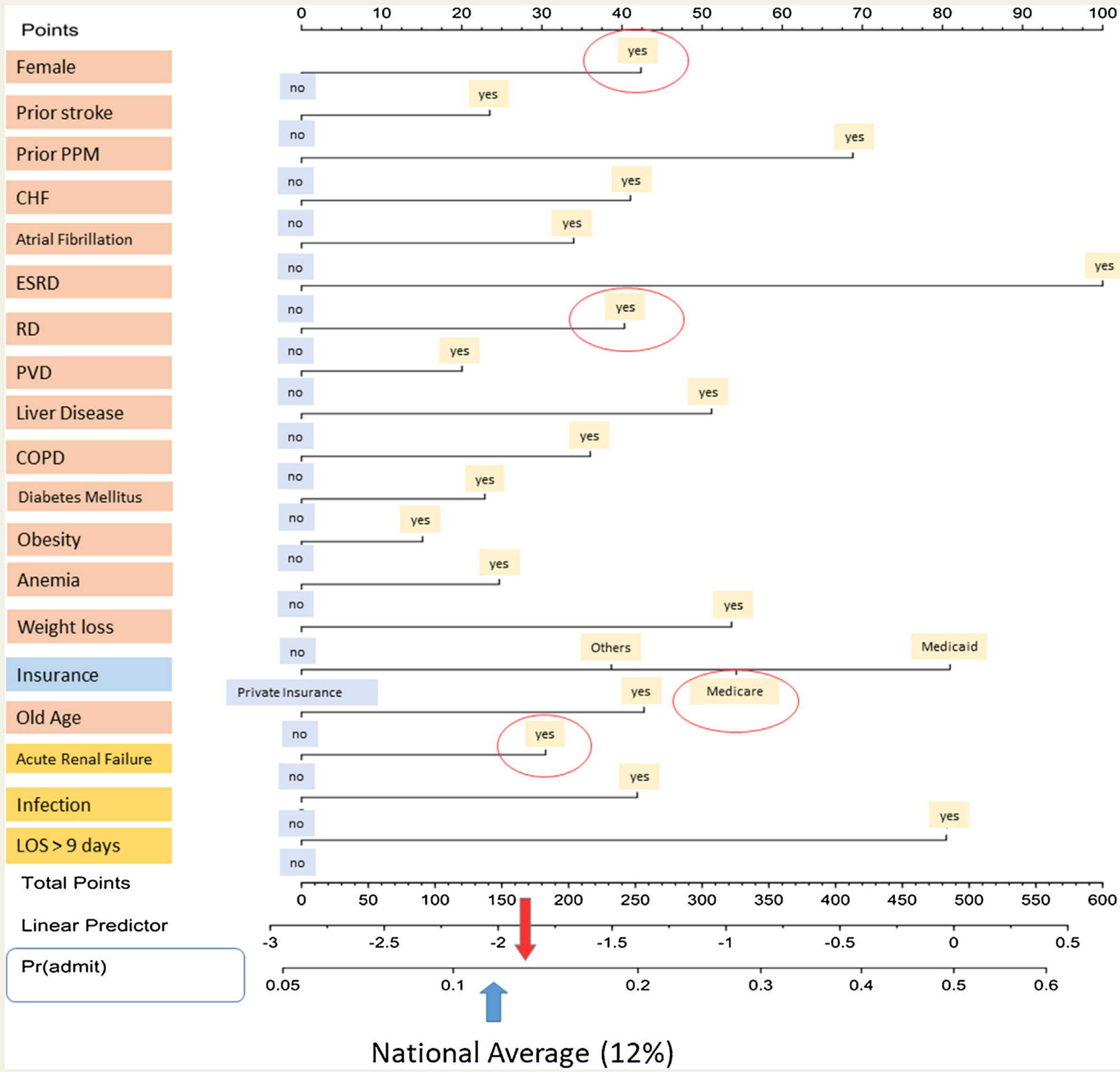

Figure 4 This figure explains use of our ruler. A 68-year-old female Medicare patient with renal dysfunction who develops acute renal failure after surgery and went home after 7 days in the hospital would have a total score of 170 (*female (40) + renal dysfunction (40) + Medicare (60) + acute renal failure (30) = 170*). This would correspond to an approximately 13–14% probability of readmission.
Abbreviations: CHF, congestive heart failure; ESRD, end stage renal disease; RD, renal dysfunction; PVD, peripheral vascular disease; COPD, chronic obstructive pulmonary disease; LOS, length of stay.

readmission for any individual patient. We believe that this knowledge could help physicians select appropriate care pathways through home health care, temporary transition to a skilled nursing facility, etc. Such tools would be helpful to reduce readmissions, improving both patient satisfaction as well as reducing the hospital cost burden.

Methodological Considerations and Limitations

Our study is based on an administrative database and hence depends upon proper ICD coding. As hospital reimbursement is related to ICD and other modifiers supplied to insurance providers, we can be fairly comfortable that due diligence has been done in documentation for each admission. Another significant benefit of using the NRD data, unlike the Medicare data, is the ability to obtain information regarding admissions from all insurance coverage cohorts and all ages. While the use of administrative data may hinder the ability to obtain more specific preoperative information like left ventricular ejection fraction or baseline creatinine, CMS actually use ICD-9 codes to determine readmission O/E ratio for each health care system. Thus, we believe that risk prediction models developed from administrative datasets are important clinical tools.

The NRD accurately captures readmission irrespective of whether the patient was readmitted to the same hospital where they were underwent operation. We feel that this is another advantage of a national level database over an Institutional one, which may inaccurately underestimate readmissions.

Conclusions

We used NRD data to develop a simple calculator for predicting 30-day readmission risk after primary CABG. Because CMS uses ICD codes for determining the readmission rates of individual hospitals and subsequent readmission penalties, our model, based on these very ICD codes, represents an important strategic decision support tool to help hospitals reduce their readmission rates and improve quality of care.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.hlc.2018.11.007.

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