American Heart Journal Plus: Cardiology Research and Practice 28 (2023) 100285

Contents lists available at ScienceDirect

American Heart Journal Plus: Cardiology Research and Practice

journal homepage: www.sciencedirect.com/journal/american-heart-journal-plus-cardiology-research-and-practice

Research paper

Derivation and validation of predictive indices for cardiac readmission after coronary and valvular surgery – A multicenter study☆

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ARTICLE INFO

Keywords:
Cardiac surgery
Coronary artery bypass grafting
Aortic valve replacement
Cardiac readmission
Predictive modeling

ABSTRACT

Objective: To derive and validate models to predict the risk of a cardiac readmission within one year after specific cardiac surgeries using information that is commonly available from hospital electronic medical records.
Methods: In this retrospective cohort study, we derived and externally validated clinical models to predict the likelihood of cardiac readmissions within one-year of isolated CABG, AVR, and combined CABG+AVR in Ontario, Canada, using multiple clinical registries and routinely collected administrative databases. For all adult patients who underwent these procedures, multiple Fine and Gray subdistribution hazard models were derived within a competing-risk framework using the cohort from April 2015 to March 2018 and validated in an independent cohort (April 2018 to March 2020).
Results: For the model that predicted post-CABG cardiac readmission, the c-statistic was 0.73 in the derivation cohort and 0.70 in the validation cohort at one-year. For the model that predicted post-AVR cardiac readmission, the c-statistic was 0.74 in the derivation and 0.73 in the validation cohort at one-year. For the model that predicted cardiac readmission following CABG+AVR, the c-statistic was 0.70 in the derivation and 0.66 in the validation cohort at one-year.
Conclusions: Prediction of one-year cardiac readmission for isolated CABG, AVR, and combined CABG+AVR can be achieved parsimoniously using multidimensional data sources. Model discrimination was better than existing models derived from single and multicenter registries.

1. Introduction

Cardiac surgery is an advancing field with steady improvements in surgical techniques, perioperative care and patient outcomes over the past few decades [1,2]. Nonetheless, readmission rates after cardiac surgery remain highest among all surgical specialties. Thirty-day readmissions occurred in one in five cases in the early 2000's and one in ten in more recent years [3–5]. A recent population-based study reported

Abbreviations: AVR, aortic valve replacement; CABG, coronary artery bypass graft; CIHI, Canadian Institute for Health Information; COPD, chronic obstructive pulmonary disease; DAD, Canadian Institute for Health Information Discharge Abstract Database; HR, hazard ratio; HFRS, Hospital Frailty Risk Score; ICD-10, International Classification of Diseases, Tenth Revision; LAD, left anterior descending; LM, left main; LVEF, left ventricular ejection fraction; OHIP, Ontario Health Insurance Plan; PCI, percutaneous coronary intervention; NYHA, New York Heart Association.

☆ Place of research study: Toronto, ON, Canada

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https://doi.org/10.1016/j.ahjo.2023.100285
Received 18 April 2022; Received in revised form 1 February 2023; Accepted 28 February 2023
Available online 3 March 2023

cardiovascular decompensation as the most common reason for readmissions that accounted for 32.2 % of all readmitted cases in Ontario. This is followed by pulmonary complications (14.5 %) and surgical site infection (9.8 %) [3].

Readmissions have been designated as a key quality metric in the care of cardiac surgery patients, due to its impact on patient quality of life as well as the planning of healthcare resources [6]. Strategies to prevent patient readmissions include close outpatient surveillance through telemonitoring and provision of home care within the first year after surgery [7,8]. To personalize these interventions during and beyond the perioperative period, accurate prediction of risk is essential. To date, prediction models have mostly been derived from single center data, focused primarily on coronary artery bypass grafting (CABG), and/or had limited predictive performance [4,9–12]. The only population-based model that covered the scope of cardiac procedures pertained to all-cause readmissions and was limited to the first 30 postoperative days. It was also modest in its discriminative ability (c-statistic = 0.63) [3].

The primary objective of our population-based retrospective cohort study was to derive and validate procedure-specific models to predict the risk of a cardiac readmission within one year after cardiac surgery. As a secondary objective, we endeavored to develop models that use variables that are commonly available and potentially extractable from hospital electronic medical records.

2. Methods

2.1. Data sharing

The dataset from this study is held securely in coded form at ICES (formerly the Institute for Clinical Evaluative Sciences). ICES is an independent, non-profit research institute funded by an annual grant from the Ontario Ministry of Health and the Ministry of Long-Term Care. As a prescribed entity under Ontario's privacy legislation, ICES is authorized to collect and use health care data for the purposes of health system analysis, evaluation and decision support. Secure access to these data is governed by policies and procedures that are approved by the Information and Privacy Commissioner of Ontario. While legal data sharing agreements between ICES and data providers (e.g., healthcare organizations and government) prohibit ICES from making the dataset publicly available, access may be granted to those who meet pre-specified criteria for confidential access, available at www.ices.on.ca/DAS (email: das@ices.on.ca).

2.2. Study design and population

We conducted a population-based, retrospective cohort study of patients 18 years and older, who underwent isolated CABG, isolated surgical AVR or combined CABG+AVR between April 1, 2015 and March 31, 2020 in Ontario, Canada [13,14]. Procedure type was identified using the CorHealth Ontario clinical registry. CorHealth is a provincial organization that provides strategic leadership to improve cardiac, stroke and vascular care, with a mandate to collect demographic, clinical and perioperative information on all patients who undergo cardiovascular procedures and related cardiac interventions in Ontario [15,16]. It captures demographic, comorbidity and procedural-related information and has been validated through selected chart audits. In addition, CorHealth Ontario ejection fraction and angiographic data undergo core laboratory validation [17].

Our derivation cohort was comprised of patients who underwent cardiac surgery between April 1, 2015, and March 31, 2018. The validation cohort was comprised of patients who underwent procedures between April 1, 2018, and March 31, 2020. For each patient, only the first procedure in a given fiscal year was considered. Procedure type was confirmed by using Canadian Classification of Health Interventions procedure codes, through linkage to the Canadian Institute for Health Information (CIHI) Discharge Abstract Database (DAD), which contains demographic, diagnostic and procedural information from all acute care hospitalizations in Ontario; and the Ontario Health Insurance Plan (OHIP) Physician Claims Database, which contains information from nearly all physician encounters, diagnostic tests and outpatient laboratory services performed in Ontario. Patients whose type of surgery could not be confirmed through DAD or OHIP, and those with other concomitant cardiac procedures, were excluded.

2.3. Outcome

Our primary outcome was cardiac hospitalizations, as captured from the DAD and defined by hospital admission for myocardial infarction, unstable angina, heart failure, coronary revascularization by percutaneous coronary intervention or CABG; and for the AVR and CABG+AVR models only, endocarditis. We conducted our analysis with death as a competing risk. Mortality was captured through the Registered Persons Database, which is a registry maintained by the Ontario Ministry of Health containing demographic and vital statistics of all residents.

2.4. Candidate variable selection

Potential variables to be entered in the model were identified from literature review as well as expert consensus, and were structured in such a way that they could be extracted from electronic data sources (e.g., administrative data, hospital records or electronic laboratory data) [18–22]. In addition to key demographic variables (age, sex and ethnicity), a list of 63 variables was developed and forwarded to members of the CorHealth Ontario Cardiac Surgery Risk Adjustment Task Force for further selection through a modified-Delphi process [23,24]. The Task Force is comprised of clinical, administrative and system-level leadership, with representatives from cardiac surgery centers across the province. It serves to advise CorHealth Ontario on the key quality indicators and clinical variables to be used in the monitoring and reporting of quality of care and outcomes of cardiac surgery. Respondents were first asked to rate each of the variables as important or not in the risk stratification process (Supplemental Table 1). Where an organization had more than one representative in the task group, one electronic survey was asked to be returned on behalf of all its members. Respondents were also able to suggest variables not already on the list. A summary of results from responses received from 7 of 11 organizations (64 % response rate), was then reviewed in a subsequent task force teleconference with representation from all centers, where a final list of 57 candidate variables was achieved through consensus-based discussion. Further refinement to combine similar or related variables (e.g., prior stroke with prior transient ischemic attack), and remove variables with numbers too few to support stable estimates, resulted in 35 candidate variables for model development (34 for the CABG model and 33 for the AVR and CABG+AVR models), including a measure of frailty using the Hospital Frailty Risk Score (HFRS) (Supplemental Table 2) [25]. The HFRS is a validated score whose purpose is to identify individuals at risk of adverse health outcomes such as mortality, long hospital stays and readmissions [25]. The score is calculable on all patients admitted to hospital (as in our study population) using an algorithm based on the International Statistical Classification of Diseases and Related Health Problems; Tenth Revision (ICD-10) coding system which assigns and sums points for selected diagnoses found patients' hospital admission records [26].

2.5. Data sources

Data sources for candidate variables are provided in Supplemental Table 2. In addition to identifying our study population, the CorHealth Registry, DAD, the CIHI Same-day Surgery database and National Ambulatory Care Reporting System, and the OHIP database were also used to obtain baseline demographics and comorbidities [27,28]. Other data sources included Ontario Laboratories Information System for

laboratory information; the Ontario Cancer Registry for cancer history; and Ontario Visible Minority Database for ethnicity [29]. These datasets were linked using unique, encoded identifiers and analyzed at ICES. The use of these data was authorized under section 45 of Ontario's Personal Health Information Protection Act, which does not require review by a Research Ethics Board.

2.6. Statistical analysis

Continuous variables are expressed as mean (standard deviation) and categorical variables as number (proportions). Outcomes were assessed through March 31, 2020. Patients were censored when they were no longer eligible for Ontario health insurance. The prediction of cardiac readmission was accomplished using multiple Fine and Gray sub-distribution hazard models within a *competing risk framework* [30]. Candidate variables were included in each of these models if their univariate P-values were <0.25, and retained if they were significant at $P < 0.05$ in the backward elimination model [31]. Details on missing data are presented in Supplemental Table 3. Missingness was assumed to be at random. Where missing, values were imputed using the procedure and sex-specific cohort mean (Supplemental Table 2). Resulting models were reviewed for face and content validity and final covariates selected based on statistical and clinical importance. For continuous variables, their association with one-year cardiac readmission was examined using cubic spline analyses with five knots at percentiles 5, 27.5, 50, 72.9 and 95 [32]. Variables with a linear relationship (age, body surface area, hematocrit, leukocytes) were entered into the models as continuous values, whereas non-linear variables (HFRS, body mass index, platelets) were treated categorically based on their distribution in tertiles and clinically meaningful ranges [25,33]. We reported hazard ratios, 95 % confidence intervals and P-values for final covariates in each model.

In both derivation and validation cohorts, model discrimination was evaluated using the c-statistic. For internal validation, optimism-corrected c-statistics from 250 bootstrap samples were drawn with replacement from the derivation cohort. Calibration was assessed using the Brier score and a calibration plot with comparison of observed versus expected mortality rates across deciles of expected risk. Analyses were performed using SAS 9.4 (SAS Institute, Cary, NC) and R studio version 1.1.456, with statistical significance defined by a two-sided P-value of <0.05.

2.7. Sensitivity analysis

We conducted two post-hoc sensitivity analyses. First, we combined left main or proximal left anterior descending artery (LAD) disease with previous sternotomy into a single variable in the model that predicted readmissions after isolated AVR. Second, we compared the performance of our procedure-specific, cardiac readmissions model to that of an omnibus, all-cause readmissions model [3], applying coefficients in the latter to our datasets.

3. Results

The population size and event rates for patients who underwent CABG, AVR, and combined CABG+AVR in the derivation and validation cohorts are summarized in Table 1 and cumulative incidence function curves for cardiac readmission in Supplemental Fig. 1. Across all patient groups, the incidence of one-year cardiac readmission was similar in the validation as compared to the derivation cohorts. The baseline characteristics were also similar across all groups (Supplemental Tables 4–6).

3.1. Predictors of one-year cardiac readmission after isolated CABG

In the derivation cohort, a total of 1123 (5.66 %) patients were readmitted for cardiac causes within one-year of hospital discharge after CABG. This number was 827 (6.24 %) in the validation cohort (Table 1). Of the candidate covariates evaluated, older age, female sex, ethnicity, frailty, body surface area, urgent inpatient surgery, moribund status (i.e., American Society of Anesthesiologists physical status classification class 5) [34], $\geq$50 % stenosis in the left main (LM) or $\geq$70 % stenosis in the proximal LAD, reduced left ventricular ejection fraction (LVEF), New York Heart Association (NYHA) functional status, atrial arrhythmia, diabetes, hypertension, cerebrovascular disease, smoking status, chronic obstructive pulmonary disease (COPD), renal insufficiency, dialysis dependence, anemia, leukocytosis, and a history of prior sternotomy or percutaneous coronary intervention (PCI) were predictors of readmission after CABG (Table 2).

Metrics of model discrimination and calibration at 30 days, 90 days and 1 year after CABG are presented in Table 3. The c-statistic at one-year was 0.73 in the derivation dataset and 0.70 in the validation dataset, indicating good discrimination. Fig. 1a shows the calibration plot of observed vs. expected rates of one-year post-CABG cardiac readmission according to each decile of risk. The model tended to slightly underestimate risk in most risk deciles.

3.2. Predictors of one-year cardiac readmission after isolated AVR

A total of 161 (5.63 %) patients in the derivation cohort, and 91 (5.01 %) in the validation cohort were readmitted for cardiac causes within one-year of isolated AVR (Table 1). The multivariable predictors of cardiac readmission after isolated AVR were ethnicity, frailty, body mass index, urgent inpatient status, presenting with acute coronary syndrome at time of isolated AVR, LM or proximal LAD stenosis, NYHA functional status, a history of hypertension, atrial arrhythmia, COPD,

Table 1
Population size and number of cardiac readmissions.[a]

Procedure	Cohort/procedure date	Population size	30-day cardiac readmission	90-day cardiac readmission	1-year cardiac readmission	
			n (%)	n (%)	n (%)	Per 100 person-years
CABG	Derivation cohort					
	April 1, 2015–March 31, 2018	19,832	364 (1.84)	604 (3.05)	1123 (5.66)	5.96
	Validation cohort					
	April 1, 2018–March 31, 2020	13,255	338 (2.55)	555 (4.19)	827 (6.24)	7.75
AVR	Derivation cohort					
	April 1, 2015–March 31, 2018	2859	73 (2.55)	107 (3.74)	161 (5.63)	5.96
	Validation cohort					
	April 1, 2018–March 31, 2020	1816	40 (2.20)	62 (3.41)	91 (5.01)	6.15
CABG + AVR	Derivation cohort					
	April 1, 2015–March 31, 2018	2279	49 (2.15)	81 (3.55)	154 (6.76)	7.25
	Validation cohort					
	April 1, 2018–March 31, 2020	1300	49 (3.77)	70 (5.38)	93 (7.15)	8.92

Abbreviations: AVR, aortic valve replacement; CABG, coronary artery bypass graft.

[a] Cardiac readmission is defined as a hospital admission for myocardial infarction, unstable angina, heart failure, coronary revascularization by percutaneous coronary intervention or CABG, and for the AVR and CABG+AVR models only, endocarditis.

Table 2
Multivariable models after backward selection.

Covariate	Parameter	HR (95 % CI)	Standard error	P-value
CABG				
Age on procedure date	0.0167	1.02 (1.01, 1.02)	0.0038	<0.0001
Male sex	−0.3925	0.68 (0.58, 0.79)	0.0777	<0.0001
Ethnicity				
Chinese	0.4264	1.53 (1.02, 2.31)	0.2092	0.042
South Asian	0.0341	1.03 (0.78, 1.38)	0.1467	0.82
Other	Ref			
Previous stroke or transient ischemic attack	0.2541	1.29 (1.04, 1.60)	0.1117	0.023
Chronic lung disease	0.2568	1.29 (1.08, 1.55)	0.0920	0.005
History of dialysis	−0.4589	0.63 (0.43, 0.92)	0.1939	0.018
Hypertension	0.3696	1.45 (1.15, 1.82)	0.1157	0.001
Diabetes	0.2622	1.30 (1.15, 1.47)	0.0627	<0.0001
Body surface area, per m^3	0.3899	1.48 (1.10, 1.98)	0.1494	0.009
Smoking history				
Current	0.1482	1.16 (0.98, 1.37)	0.0838	0.08
Former	0.0105	1.01 (0.88, 1.16)	0.0708	0.88
Never	Ref			
Creatinine (μmol/L)				
0–119 or missing	Ref			
120–179	0.4044	1.50 (1.26, 1.78)	0.0876	<0.0001
180+	0.5635	1.76 (1.36, 2.27)	0.1305	<0.0001
Hematocrit, per 1 %	−3.5001	0.03 (0.01, 0.12)	0.7119	<0.0001
Leukocytes, per 10^3	0.0212	1.02 (1.00, 1.05)	0.0119	0.08
Previous sternotomy	0.3405	1.41 (0.99, 1.99)	0.1785	0.06
Previous PCI	0.2444	1.28 (1.10, 1.48)	0.0769	0.002
Moribund	0.4500	1.57 (1.14, 2.17)	0.1646	0.006
NHYA class				
1 or no symptoms/ missing/unknown	−0.5383	0.58 (0.41, 0.82)	0.1742	0.002
2	−0.0334	0.97 (0.67, 1.39)	0.1857	0.86
3	−0.0967	0.91 (0.62, 1.33)	0.1958	0.62
4	Ref			
Wait at home (ref: wait in hospital)	−0.2834	0.75 (0.65, 0.87)	0.0723	<0.0001
Atrial fibrillation or flutter	0.3318	1.39 (1.18, 1.64)	0.0843	<0.0001
Left ventricular ejection fraction				
≥50 %	Ref			
35–49 %	0.2030	1.23 (1.06, 1.41)	0.0734	0.006
20–34 %	0.5237	1.69 (1.41, 2.03)	0.0929	<0.0001
<20 %	0.6708	1.96 (1.37, 2.78)	0.1803	0.0002
Missing	0.1193	1.13 (0.85, 1.50)	0.1465	0.42
Left main or proximal LAD disease	−0.1007	0.90 (0.79, 1.03)	0.0659	0.13
Hospital Frailty Risk Score				
0–0.9	Ref			
1.0–3.0	0.2826	1.33 (1.10, 1.60)	0.0944	0.003
>3.0	0.5944	1.81 (1.51, 2.17)	0.0915	<0.0001
AVR				
Chronic lung disease	0.7550	2.13 (1.50, 3.01)	0.1767	<0.0001
Hypertension	0.4126	1.51 (0.94, 2.44)	0.2443	0.0913
Body mass index, per kg/ m^2	0.0241	1.02 (1.00, 1.05)	0.0108	0.0259
Hematocrit, per 1 %	−3.3213	0.04 (0.00, 1.04)	1.7165	0.0530
Acute coronary syndrome	−0.8206	0.44 (0.18, 1.09)	0.4640	0.0770
NHYA class				
1 or no symptoms/ missing/unknown	−0.1229	0.88 (0.44, 1.77)	0.3548	0.7290
2	0.0234	1.02 (0.50, 2.08)	0.3617	0.9484
3	0.3624	1.44 (0.73, 2.81)	0.3428	0.2904
4	Ref			
Wait at home (ref: wait in hospital)	−0.7479	0.47 (0.33, 0.67)	0.1803	<0.0001
Atrial fibrillation or flutter	0.4268	1.53 (1.10, 2.14)	0.1699	0.0120
Left main or proximal LAD disease	0.7012	2.02 (0.94, 4.31)	0.3875	0.0704
Hospital Frailty Risk Score				
0–0.9	Ref			
1.0–3.0	0.6070	1.83 (1.19, 2.84)	0.2227	0.0064
>3.0	0.6931	2.00 (1.33, 3.00)	0.2071	0.0008
CABG + AVR				
Chronic lung disease	0.5918	1.81 (1.18, 2.78)	0.2192	0.007
Diabetes	0.4294	1.54 (1.11, 2.13)	0.1671	0.010
Body surface area, per m^3	0.6704	1.95 (0.98, 3.92)	0.3548	0.06
Smoking history				
Current	−0.1340	0.87 (0.54, 1.42)	0.2473	0.59
Former	−0.3568	0.70 (0.49, 1.00)	0.1840	0.05
Never	Ref			
Hematocrit, per 1 %	−3.1180	0.04 (0.00, 1.09)	1.6350	0.06
Previous PCI	0.3759	1.46 (0.97, 2.18)	0.2059	0.07
Moribund	0.6068	1.83 (0.88, 3.82)	0.3741	0.10
NHYA class				
1 or no symptoms/ missing/unknown	−0.7464	0.47 (0.26, 0.88)	0.3148	0.018
2	−0.3957	0.67 (0.37, 1.24)	0.3107	0.20
3	−0.5009	0.61 (0.33, 1.13)	0.3163	0.11
4	Ref			
Atrial fibrillation or flutter	0.4934	1.64 (1.14, 2.35)	0.1834	0.007
Hospital Frailty Risk Score				
0–0.9	Ref			
1.0–3.0	0.7184	2.05 (1.27, 3.33)	0.2466	0.004
>3.0	0.6888	1.99 (1.28, 3.10)	0.2251	0.002

Abbreviations: AVR, aortic valve replacement; CABG, coronary artery bypass graft; HR, hazard ratio; LAD, left anterior descending; NYHA, New York Heart Association; PCI, percutaneous coronary intervention.

anemia and dialysis-dependence (Table 2).

At one-year, the c-statistic was 0.74 in the derivation sample and 0.73 in the validation sample (Table 3). The calibration plot of observed vs. expected rates of one-year post-AVR cardiac readmission according to each decile of risk is presented in Fig. 1b. The model tended to overestimate risk in the highest risk decile.

3.3. Predictors of one-year cardiac readmission after combined CABG + AVR

A total of 154 (6.76 %) patients in the derivation cohort, and 93 (7.15 %) in the validation cohort were readmitted for cardiac causes within one-year of combined CABG+AVR (Table 1). Multivariable predictors of cardiac readmission were BSA, moribund status, NYHA functional status, previous PCI, atrial arrhythmia, a history of smoking, COPD, diabetes and anemia (Table 2).

At one-year, the c-statistic was 0.70 in the derivation dataset and 0.66 in the validation dataset (Table 3). Fig. 1c shows the calibration plot of observed vs. expected rates of one-year cardiac readmission after combined CABG+AVR according to each decile of risk. The observed and predicted rates were similar across all except the highest risk decile, where the model tended to overestimate risk.

3.4. Sensitivity analysis

In the sensitivity analysis where we combined left main or proximal LAD disease with previous sternotomy into a single variable in the isolated AVR model, the magnitude and direction of coefficients, as well as the model's predictive performance were similar compared to those of the original model (Supplemental Table 7). In the sensitivity analysis where we compared the performance of our model with that of an omnibus, all-cause readmissions model [3], we found that our models had slightly higher discrimination for CABG and CABG+AVR, and similar discrimination for isolated AVR (Supplemental Table 8).

4. Discussion

We demonstrated that multidimensional data sources comprised of a clinical registry and administrative health databases can be used to develop one-year cardiac readmission risk prediction models for isolated CABG, isolated AVR, and combined CABG+AVR with good performance. We found that the Ontario isolated AVR model was the best performing model with a c-statistic of 0.73 at one-year, while the isolated CABG and combined CABG+AVR models also predicted well with c-statistics of 0.70 and 0.66. Importantly, the Ontario models outperformed existing models without sacrificing parsimony. Our CABG model included 23 predictor variables, while our isolated AVR and CABG+AVR models each included 13 and 10 predictors, respectively. Finally, we were able to derive these models using data that are routinely collected at teaching and community hospitals, without loss to follow up.

The Centers for Medicare and Medicaid Services designated readmissions after CABG as a key quality performance metric in 2017; with penalties imposed on hospitals with readmission rates above the United States national average [6]. Despite the importance of this initiative, its ability to inform patients of their outlook and the system of both their

Table 3
Model discrimination and calibration.

	30-day cardiac readmission		90-day cardiac readmission		1-year cardiac readmission	
	Derivation cohort	Validation cohort	Derivation cohort	Validation cohort	Derivation cohort	Validation cohort
CABG						
C-statistic	0.7199	0.6684	0.7296	0.6912	0.7267	0.7022
Brier score	0.0178	0.0247	0.0287	0.0395	0.0508	0.0597
AVR						
C-statistic	0.6753	0.6948	0.7286	0.7212	0.7355	0.7304
Brier score	0.0247	0.0217	0.0347	0.0324	0.0499	0.0487
CABG + AVR						
C-statistic	0.6835	0.6569	0.7206	0.6579	0.6962	0.6579
Brier score	0.0208	0.0360	0.0335	0.0504	0.0605	0.0675

Abbreviations: AVR, aortic valve replacement; CABG, coronary artery bypass.

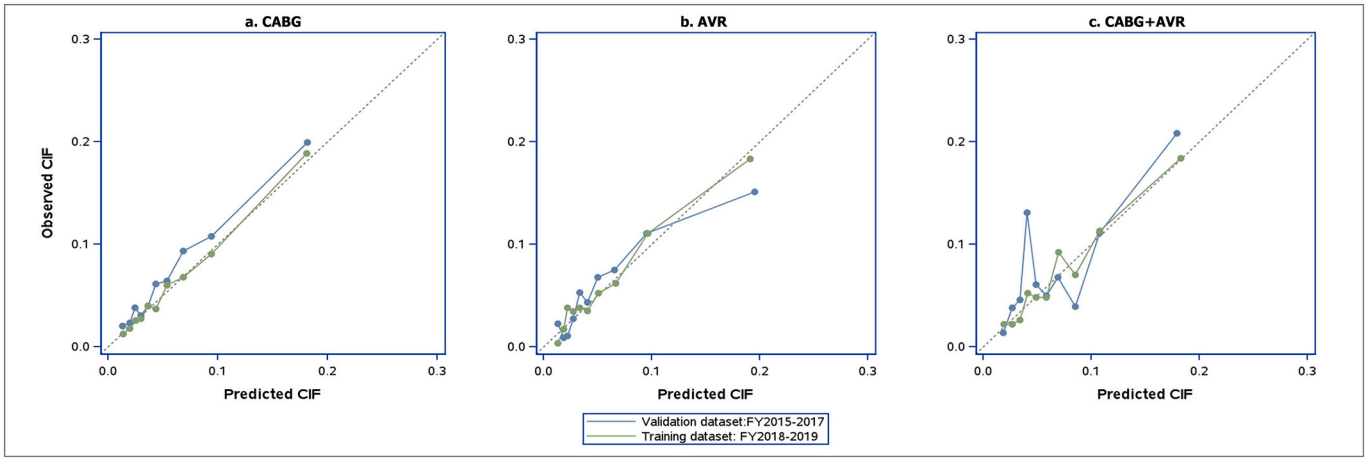

Fig. 1. Calibration plots for observed versus expected 1-year cumulative incidence of cardiac readmission by decile of expected rate and surgery type. AVR, aortic valve replacement; CABG, coronary artery bypass; CIF, cumulative incidence function; FY, fiscal year.

outlook and capacity needs has been limited by a lack of evidence-based algorithms to identify high-risk candidates. As patients presenting for cardiac surgery become increasingly complex, higher performance models are needed to inform patient-centered operative decision-making, personalize targeted interventions such as telemonitoring and home visits [7,8], and enhance health system resource planning. Prediction models to date have focused on the perioperative period, mostly in patients who underwent CABG, and predicted all-cause rather than cause-specific readmissions with only modest performance [4,9–12]. Notably, Shahian linked the Society of Thoracic Surgeons National Database to Medicare claims in over 160,000 patients undergoing CABG surgery, and reported a c-statistic of 0.65 in a model predicting 30-day all-cause readmission [12]. Other studies have added factors such as post-operative complications, insurance type and discharge destination to model the same outcome, and have reported similar performance [4,10,11]. Modeling 30-day all-cause readmission after cardiac operations more broadly, and using pre-operative and post-operative factors, Kilic reported a c-statistic of 0.63 [9]. Furthermore, in 2018, Tam et al. derived an omnibus 30-day cardiac surgery readmissions model using multicenter clinical and administrative data from Ontario. This model contained 23 variables and had a c-statistic of 0.63, which was on par with other published models [3].

Our procedure-specific, cardiac readmission models add to current knowledge by predicting readmission beyond the perioperative period where reasons for readmission may be different and are applicable to frequently-performed cardiovascular surgical procedures. Our models out-performed existing models with c-statistics ranging from 0.66 to 0.74, and had excellent calibration. Cardiac complications constituted the most common cause of readmissions after cardiac surgery, followed by pulmonary complications and wound infection; each with a unique set of patient and procedure-related risk factors [3]. The adoption of an etiology-specific modeling strategy, the inclusion of a larger pool of candidate variables along with ones of physiologic relevance (e.g., frailty) [16,35,36], likely contributed to the improved predictive performance of our models as compared to those already published. We identified moribund status, frailty, ethnicity and wait location as new risk factors for readmission. The incorporation of sociodemographic variables, as well as measures of operative priority status and baseline physiologic reserve, served to improve personalized risk prediction. Our models can be incorporated into the electronic medical record system to provide automated risk calculations to inform individualized post-discharge planning, as well as for hospital resource planning at the institutional and system level.

Aside from their role in surgical decision-making and hospital resource planning, these clinical prediction models provide risk-adjusted ratios of observed vs. expected readmission rates to enhance comparability between centers. They were intended to be used in the systematic quality reporting process, as a means for policy makers to compare outcomes across institutions [37,38]. Our research was motivated by a province-wide cardiac surgery quality improvement initiative that includes the provision of public report cards on key quality indicators for all cardiac centers in Ontario. While these reports are not released to the broader public, each cardiac surgery center does get to see the outcomes of all other surgical centers in an identifiable manner. At the hospital level, the widening use of electronic medical records may lend itself to institution-based self quality assessments of readmission risk, which could lead to better allocation of telemonitoring and other post-discharge care and follow-up strategies to reduce readmissions after cardiovascular surgical procedures. At the provincial level, these models could also be used to provide evidence-based guidance for the allocation of healthcare funding and resources.

4.1. Limitations

Our study must be interpreted in the context of several limitations. First, certain physiologic details are unavailable in the datasets used. For instance, there is evidence that the inclusion of cardiac biomarkers may improve surgical risk prediction [39]. Second, we rely on administrative data and physician billing codes to derive covariates of interest, and although our predictive models performed well in Ontario, they remain to be validated in other healthcare jurisdictions. However, the 'big data' sources used in this study and associated codes have been previously validated or published [3,29,40]. Third, our models apply to the three most commonly performed cardiac surgery procedures (i.e., isolated CABG, AVR and CABG+AVR), and the impact of other concomitant procedures such as aortic root enlargement or ascending aorta replacement were not captured. Fourth, the relative event rates for combined CABG+AVR precluded us from entering a large number of covariates during its modeling process. Despite this, our models surpassed existing models in performance and performed well in external validation. Lastly, continuous model updates are warranted to accommodate the evolving patient demographics and indications for CABG and AVR [41].

5. Conclusions

Accurate prediction of one-year cardiac readmissions for isolated CABG, isolated AVR, and combined CABG+AVR can be achieved parsimoniously using routinely collected multidimensional administrative and clinical registry datasets, with better performance than existing models. Hybridization of multidimensional data sources represents an efficient approach to data collection that have utility in quality of care evaluation and reporting. Given that readmissions are not universally preventable, information gained from this study may be used by local and regional planners to more reliably estimate subsequent hospital resource needs.

Ethical statement

The authors testify that the manuscript submitted to American Heart Journal Plus: Cardiology Research and Practice:

1. Is an accurate account of the work performed and an objective discussion of its significance;
2. Has not been published in whole or in part elsewhere;
3. Is not currently being considered for publication in another journal; and
4. That all co-authors have been personally and actively involved in substantive work leading to the manuscript, and will hold themselves jointly and individually responsible for its content.

Funding

This study was supported by ICES, which is funded by an annual grant from the Ontario Ministry of Health and the Ontario Ministry of Long-Term Care. This study also received funding from CorHealth Ontario as a part of a province-wide quality initiative and from a Foundation grant from the Canadian Institutes of Health Research (CIHR) grant # FDN 148446. Dr. Sun was named National New Investigator by the Heart and Stroke Foundation of Canada and was supported by a Clinical Research Chair in Big Data and Cardiovascular Outcomes at the University of Ottawa. Dr. Lee is the Ted Rogers Chair in Heart Function Outcomes, University Health Network, University of Toronto. Dr. Austin is supported by a Mid-Career Investigator award from the Heart and Stroke Foundation.

CRediT authorship contribution statement

Louise Y. Sun: Conceptualization, Methodology, Validation, Writing – original draft, Visualization. **Anna Chu:** Methodology, Writing – review & editing, Visualization. **Derrick Y. Tam:** Methodology, Validation, Writing – review & editing. **Xuesong Wang:** Methodology, Formal

analysis, Writing – review & editing. **Jiming Fang:** Methodology, Validation, Writing – review & editing. **Peter C. Austin:** Methodology, Validation, Writing – review & editing. **Christopher M. Feindel:** Conceptualization, Writing – review & editing. **Vicki Alexopoulos:** Writing – review & editing. **Natasa Tusevljak:** Writing – review & editing, Project administration. **Rodolfo Rocha:** Writing – review & editing. **Maral Ouzounian:** Writing – review & editing. **Graham Woodward:** Writing – review & editing, Funding acquisition. **Douglas S. Lee:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This document used data adapted from the Statistics Canada Postal CodeOM Conversion File, which is based on data licensed from Canada Post Corporation, and/or data adapted from the Ontario Ministry of Health Postal Code Conversion File, which contains data copied under license from ©Canada Post Corporation and Statistics Canada. Parts of this material are based on data and/or information compiled and provided by the Ontario Ministry of Health, the Canadian Institute for Health Information (CIHI) and Ontario Health. The authors acknowledge that the clinical registry data used in this analysis is from participating hospitals through CorHealth Ontario, which serves as an advisory body to the Ministry of Health, is funded by the Ministry of Health, and is dedicated to improving the quality, efficiency, access and equity in the delivery of the continuum of adult cardiac and stroke care in Ontario, Canada. However, the analyses, opinions, results, conclusions, and statements reported in this paper are those of the authors and do not necessarily reflect those of the Ministry of Health, CIHI, Ontario Health or the funding sources. No endorsement by ICES or the Ontario Ministry of Health or Ministry of Long-term Care is intended or should be inferred. A list of the CorHealth Ontario Cardiac Surgery Risk Adjustment Task Force is provided in Supplemental Table 9.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ahjo.2023.100285.

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