Derivation and Validation of a Clinical Model to Predict Death on the Waitlist for Cardiac Surgery

Louise Y. Sun, MD, SM; Harindra C. Wijeysundera, MD, PhD; Douglas S. Lee, MD, PhD; Sean van Diepen, MD, MSc; Marc Ruel, MD, MPH; Anan Bader Eddeen, MSc; Thierry G. Mesana, MD, PhD

From the Division of Cardiac Anesthesiology, University of Ottawa Heart Institute and the School of Epidemiology and Public Health, University of Ottawa, Ontario, Canada (LYS); Institute for Clinical Evaluative Sciences (LYS, HCW, DSL, ABE); Schulich Heart Program, Sunnybrook Health Sciences Centre; Division of Cardiology, Department of Medicine and Institute for Health Policy, Management and Evaluation, University of Toronto, Ontario, Canada (HCW); Peter Munk Cardiac Centre, University Health Network, University of Toronto, Ontario, Canada (DSL); Department of Critical Care and Division of Cardiology, Department of Medicine, University of Alberta, Edmonton, Canada (SvD); and the Division of Cardiac Surgery, University of Ottawa Heart Institute, Ontario, Canada (MR, TGM).

Address for Correspondence:

Louise Y. Sun, MD, SM, FRCPC, FAHA

Clinician Scientist and Associate Professor

Room H2410, 40 Ruskin Street, Ottawa, ON, Canada K1Y 4W7

Phone: 1 613 696 7381 Facsimile: 1 613 696 7099

Email: lsun@ottawaheart.ca

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ABSTRACT

Background: The COVID-19 pandemic has led to a global surgical backlog. This delay in access to care has resulted in unintended harm to cardiac surgery patients, who are at risk of mortality if their conditions are left untreated. To facilitate evidence-based resource allocation, we derived and validated a clinical risk score to predict death on the waitlist in patients referred for cardiac surgery.

Methods: We used the CorHealth Ontario Registry and linked ICES healthcare administrative databases with information on all Ontario residents. Included were patients ≥ 18 years of age who were referred for coronary artery bypass grafting, valvular, and/or thoracic aorta surgeries between October 1, 2008 and September 30, 2019. We used a hybrid modelling approach with Random Forests for initial variable selection, followed by backward stepwise logistic regression modelling for clinical interpretability and parsimony. We internally validated this model, termed the "CardiOttawa Waitlist Mortality Score", using 200 bootstraps.

Results: There were 269 (0.24%) waitlist deaths amongst 112,266 referrals. The model discriminated (c-statistic 0.76; 0.73 after optimism correction) and calibrated well in the overall cohort (Hosmer-Lemeshow p-value = 0.22) and across each type of surgery.

Interpretation: The CardiOttawa Waitlist Mortality Score is a simple clinical risk model that predicts the likelihood of waitlist death in patients awaiting cardiac surgery. It can be combined with the CardiOttawa Length of Stay Score to provide rapid, data-driven decision support for managing access to cardiac care and preserve system capacity during the COVID-19 crisis, the recovery period, and beyond.

Key Words: cardiac surgery, waitlist, mortality, access to care, COVID-19

INTRODUCTION

The coronavirus disease (COVID-19), which was declared a pandemic by the World Health Organization on March 11, 2020, has precipitated a health care crisis that disrupted the care of patients with cardiovascular conditions. Non-emergent cardiac procedures were deferred amidst the first wave of this crisis to ensure that sufficient resources were available to treat patients with COVID-19 (1), creating surgical backlogs around the globe (2).

This growing surgical backlog of patients with advanced cardiac disease creates a dilemma for clinicians and administrators, as these patients require monitoring in the intensive care unit (ICU) after surgery and may potentially compete with the resource needs of those with severe COVID-19 infection. Our group recently developed and validated the CardiOttawa Length of Stay (LOS) Score as an evidenced-based decision support tool to identify high and low ICU resource users after cardiac surgery (3). However, safe triage decision-making goes beyond knowing patients' postoperative health care resource needs; it requires an accurate estimation of the risks they will face in waiting for surgery. Published waitlist risk models are limited to specific populations such as patients undergoing coronary artery bypass grafting (CABG) (4) and cardiac transplantation (5). The only population-based study of waitlist deaths included a small number of events and was focused on the identification of risk factors rather than the prediction of risk (6). Consequently, current recommendations for waitlist management were developed based on expert opinion rather than clinical evidence. We conducted a population-based study in Ontario, Canada to derive and validate a clinical model to predict death on the waitlist for patients who were referred for cardiac surgery.

METHODS

LYS and ABE had full access to all the data in the study and take responsibility for its integrity and the data analysis. The dataset from this study is held securely in coded form at ICES (formerly the Institutes for Clinical Evaluative Sciences). The use of data was authorized under section 45 of Ontario's *Personal Health Information Protection Act*, which does not require review by a research ethics board (7).

Design and Population

We conducted a population-based, retrospective cohort study of adult patients ≥ 18 years of age, who were waitlisted for CABG; and/or valvular surgery; as well as surgery on the thoracic aorta in Ontario between October 1, 2008, and September 30, 2019. Excluded were patients who were waitlisted for transcatheter procedures, cardiac transplantation, or implantation of ventricular assist devices; as well as those requiring salvage procedures. For patients with multiple cardiac procedures during the study period, only the index procedure was included in the analysis.

Data Source

We used the clinical registry of CorHealth Ontario and population-level administrative healthcare databases available at ICES. CorHealth Ontario maintains a detailed prospective registry of all patients who undergo invasive cardiac procedures in Ontario, including demographic, comorbidity, and procedure-related information. CorHealth Ontario data undergo selected chart audits and core laboratory validation (3, 7-15).

Using unique confidential identifiers, we linked the CorHealth Ontario registry (detailed surgical referral and waitlist data, date and type of cardiac procedures, physiologic and comorbidity data) with

the Canadian Institute for Health Information Discharge Abstract Database (DAD; comorbidities, hospital admissions, and in-hospital procedures), the Ontario Health Insurance Plan (OHIP) database (physician service claims) and the Registered Persons Database (RPDB; vital statistics). These administrative databases have been validated for many outcomes, exposures, and comorbidities, including heart failure (HF), chronic obstructive pulmonary disease (COPD), asthma, hypertension, myocardial infarction (MI), and diabetes. Ontario is the most populous province in Canada, with ~14.6 million residents, and it is one of the most ethnically diverse jurisdictions in the world.

Potential covariates considered in the analyses are detailed in **Table 1** and included demographic, physiological, anatomical and comorbidity data, as well as information regarding the proposed procedure (operative priority status, recommended surgical wait time, preoperative cardiogenic shock, redo sternotomy, and type of surgery).

As with our previous studies (3, 7-19), height, weight, operative priority, and information pertaining to LVEF, valvular disease, and coronary anatomy were obtained from the CorHealth Ontario registry. In addition, comorbidities were identified from the CorHealth Ontario registry and supplemented with data from DAD and OHIP using International Classification of Diseases 10th Revision (ICD-10-CA) codes (20) within five years prior to the index procedure, according to validated algorithms (21-24).

Outcome

The primary outcome was all-cause mortality that occurred between the date of acceptance onto the waitlist and the date of removal from the waitlist.

Statistical Analysis

Continuous variables were compared with a 2-sample *t*-test or with a Wilcoxon rank sum test for non-normally distributed data. Categorical variables were compared with a chi-square test.

Missing Data

Left ventricular ejection fraction (LVEF) was missing in 3,197 (2.8%), preoperative serum creatinine value in 5,021 (4.5%), height in 5,795 (5.2%) and weight in 5,464 (4.9%) patients. No other data were missing. The missing values were imputed using multiple imputations with fully conditional (Markov chain Monte Carlo [MCMC]) methods (25). Specifically, logistic regression modelling was used to generate five imputed datasets within the SAS "proc MI" framework, where missing values were predicted drawing on all candidate covariates. Each imputation provided a complete dataset, reflecting the distributions and correlations between variables.

Model Development

We used a hybrid approach of Random Forests for initial variable selection, followed by stepwise logistic regression for clinical interpretability and parsimony. Details of the Random Forests method have been described elsewhere (26-28). In short, we used a bootstrap sample of the data to build each of the classification trees. A random subset of variables was selected at each split, thereby constructing a large collection of decision trees with controlled variation. The trees are left unpruned in order to minimize bias. Every tree in the forest casts a "vote" for the best classification for a given observation, and the class receiving the most votes results in the prediction for that specific observation. The dataset was first sampled to create an in-bag partition (2/3 of derivation sample) to construct the decision tree, and a smaller out-of-bag partition (1/3 of derivation sample) to test the constructed tree to evaluate its performance. Random Forests calculates estimates of variable importance for classification

using the permutation variable importance measure (26), which is based on the decrease of classification accuracy when values of a variable in a node of a tree are permuted randomly. Our model was based on 500 classification trees and 6 variables available for splitting at each tree node.

We identified a subset of the top 30 predictor variables out of the 40 candidate variables and incorporated them into a logistic model. According to methods described by Harrell and colleagues (29), predictor variables with univariate *P*-values of < 0.10 were entered into a multivariable stepwise logistic regression model based on both clinical and statistical significance. We used a backward variable selection algorithm, retaining in the final model covariates with *P*-values of < 0.05 as well as those deemed to be clinically important. The final prediction model was termed the CardiOttawa Waitlist Mortality Score.

Model Evaluation

Model discrimination was evaluated using the c-statistic. An optimism-corrected c-statistic was obtained from 200 bootstrap samples drawn with replacement from the study sample. The Youden index was used to determine optimal cut-off points for calculating measures of validity, including sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) (30). Calibration was assessed using the Hosmer–Lemeshow chi-square statistic, the Brier score (29), and a comparison of observed versus expected mortality rates within quintiles of expected risk in the overall cohort, as well as across different subgroups according to the type of surgery.

We used the "RandomForest" package for R (version 3.6.3, R Foundation, New Zealand), as well as SAS version 9.4 (SAS Institute, Cary, NC). Statistical significance was defined by a two-sided *P*-value of < 0.05.

RESULTS

Among the 112,266 patients referred for cardiac surgery, 269 (0.24%) died while on the waitlist. Of these waitlist deaths, 118 (0.16%) occurred while awaiting isolated CABG, 81 (0.33%) while awaiting valve procedures, 63 (0.51%) while awaiting combined CABG/valve procedures, and 7 (0.21%) while awaiting thoracic aorta procedures. The median wait time was 13 (IQR, 4-38) days overall and was 7 (3-26) days for CABG, 32 (12-62) days for valvular surgery, 21 (7-46) days for combined CABG/valve, and 35 (9-64) days for thoracic aorta procedures.

Compared with patients who survived the waitlist period, those who died were older; more likely to have had a high-risk ACS; to have reduced LVEF, HF, aortic or mitral regurgitation warranting operative intervention, severe aortic stenosis, comorbidities such as diabetes, cerebrovascular disease, peripheral arterial disease, renal and liver dysfunction, anemia, or psychosis; to be scheduled for urgent, reoperative valvular or combined CABG/valve surgery with shorter recommended wait times, and to present with unanticipated cardiogenic shock prior to the scheduled procedure (**Table 1**).

Predictors of Waitlist Mortality

The accuracy of the Random Forests model was 76%. The resulting top 30 predictor variables are summarized in **Supplemental Figure S1**. After we applied stepwise logistic regression to achieve parsimony, the final model consisted of 11 variables (**Table 2**). Sex, type of surgery, LM-equivalent anatomy, and CCS classification were forced into the model on the basis of clinical significance. Other multivariable predictors of waitlist mortality were age, LVEF, history of HF, atrial fibrillation, dialysis, psychosis, and operative priority.

Model Performance

The c-statistic of the multivariable model was 0.76. After optimism correction, the c-statistic was 0.73, the Hosmer–Lemeshow chi-square statistic was 10.76 ($P = 0.22$), and the Brier score was 0.0024. **Table 3** shows the observed rates of waitlist mortality according to each risk quintile. The lowest risk quintile had a waitlist mortality of 0.058% (95% CI, 0.024-0.094%), while the highest quintile had a waitlist mortality of 0.67% (95% CI, 0.56-0.76%). The observed and predicted numbers of waitlist deaths were similar across all probability quintiles. The model was highly calibrated within each category of surgery (**Figure 1**). The receiver-operating characteristic curve for the CardiOttawa Waitlist Mortality model is presented in **Figure 2**. The optimal cut-off point on the ROC curve was at a predicted probability of 0.24%, with the following characteristics: sensitivity, 69.1%; specificity, 72.1%; PPV, 0.59%; NPV, 99.9%.

Sensitivity Analysis

Post-hoc, we investigated the procedures for which operative priority was unknown. We found that all of these cases were booked as thoracic aorta surgery. We then imputed the operative priority status for these procedures and followed the same modelling approach as described above. The final model (**Supplemental Table S1**) was similar to the original model, with a c-statistic of 0.75 (0.72 after optimism correction), Hosmer-Lemeshow chi-square statistic of 8.00 ($P = 0.43$), and Brier score of 0.0024.

CardiOttawa Waitlist Mortality Score

The β-coefficients for the final model are presented in **Table 2** (online calculator available at https://cardiottawa.ottawaheart.ca/).

DISCUSSION

Waitlist management for high-risk patients such as those needing cardiac surgery is an ongoing challenge for clinicians and administrators in Canada and other publicly-funded healthcare systems around the world, where access to these procedures is limited by surgical capacity (6). The cardiac surgery waitlist has grown during the COVID-19 pandemic through lengthening wait times (1) and delayed disease presentation due to missed cardiac specialist visits (31, 32). As the pandemic evolves and when it ultimately ends, evidence-based criteria are needed to facilitate timely and efficient resource allocation to address this global surgical backlog.

The few existing waitlist risk algorithms were either single-center, included small numbers of events, or were tailored to specific populations such as patients awaiting CABG or heart transplantation. The only contemporary study of waitlist mortality that broadly encompassed major types of cardiac procedures was limited to risk factor identification. The current Canadian cardiac surgical wait time benchmarks were developed based on expert opinion in 2005 and has limited ability to prevent waitlist deaths (6). In fact, a recent study that investigated 101 cardiac surgery waitlist deaths in Alberta, Canada found that many patients died within the CCS recommended waitlist timeframes (6). A recent statement from the Canadian Society of Cardiac Surgeons highlighted "it is critically important that cardiac surgeons ensure the presence of a robust wait-times database at their institutions that captures rates of adverse events in these patients while on the waitlist so that decisions around the reallocation of resources may be made in a timely fashion" (33). Despite the need for a data-driven waitlist assessment tool to improve patient care, the triage classification system proposed in this recommendation had not been tested using real-world data (34).

We developed the CardiOttawa Waitlist Mortality Score to provide triage decision support for cardiac surgery patients, using variables that are readily available at the time of surgical referral. The

CardiOttawa was derived and validated on a large and representative population. It discriminates well, has excellent calibration across all types of surgery, and is to our knowledge the first predictive algorithm that applies to a broad range of cardiac surgical procedures. In comparison, the study by Senaratne *et al.* found that CCS recommended wait times poorly discriminated waitlist mortality across a similar variety of proposed cardiac procedures (c-statistic = 0.577) (34). A smaller, single-center Scandinavian study that produced a mortality risk score from 42 CABG waitlist deaths did not report performance metrics for the model (4).

Current waitlist recommendations are based primarily on anatomic factors such as coronary and valvular heart disease. The CardiOttawa predictor variables are consistent with those identified in the literature (4-6, 35) and capture important information on baseline patient factors (demographic, medical conditions, hemodynamic stability) as well as proposed surgical information, in addition to anatomic factors. Whereas the CCS recommended cardiac procedure wait times are likely too long to ensure patient safety, the CardiOttawa Waitlist Mortality Score has the potential to reduce patient mortality through better risk stratification at the time of referral. This waitlist score could be combined with the CardiOttawa LOS Score (3) to identify high-risk patients and enable evidence-based surgical scheduling to optimize postoperative ICU resource use. The combined risk calculator termed the CardiOttawa 2.1: COVID Triage Tool can be accessed at https://cardiottawa.ottawaheart.ca. The caveat that applies to all decision-support tools is pertinent because the CardiOttawa Waitlist Mortality Score is intended to assist the clinician, who should ultimately synthesize the predictive score with clinical judgment in making decisions.

Strengths and Limitations

Major strengths of our waitlist mortality tool are that it was derived from a large, ethnically diverse population, its high degree of calibration across a broad spectrum of cardiac surgeries, and its suitability for use at the time of surgical referral. As it is intended to guide waitlist triage decisions, it is important that the model be validated in a patient sample that is representative of the population for which the tool will be used. Our study has some limitations. *First*, universal drug coverage is only available to Ontario residents aged 65 years and older, and thus we were not able to include information on prescription medications for all patients in the modelling process. However, medications have not routinely been incorporated in cardiac surgical risk models to date. In addition, model simplicity is an important element of decision-support tools, and thus it is better to carefully select potential factors rather than to incorporate an exhaustive list. *Second*, certain detailed physiologic measures such as brain natriuretic peptide were lacking in the databases used. However, brain natriuretic peptide is not routinely measured in the perioperative setting. *Third*, the low event rates within each type of surgery preclude procedure-specific modelling. Nonetheless, a multicenter, omnibus risk model is efficient and practical, as operating time is a shared resource.

CONCLUSIONS

The CardiOttawa Waitlist Mortality Score is a simple clinical risk model that predicts the likelihood of waitlist deaths in patients awaiting major cardiac surgery. The importance of this predictive model is underscored by the inclusion of a population-based sample and its excellent calibration across all procedure types. It can be combined with the CardiOttawa LOS Score to provide rapid, data-driven decision support for clinicians, hospital administrators, and policy-makers as they manage access to cardiac care and preserve system capacity during the COVID-19 crisis, the recovery period, and beyond.

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FIGURE LEGENDS

Figure 1. Observed vs. expected waitlist deaths by type of cardiac surgery.

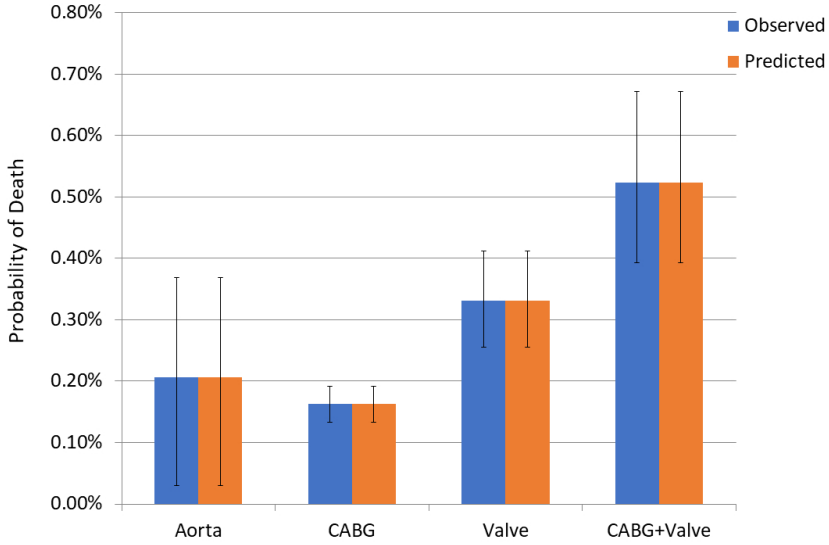
Legend: The error bars indicate 95% confidence intervals and were obtained through 200 bootstraps.

Figure 2. Receiver-operating characteristic curve of the CardiOttawa Waitlist Score model.

SUPPLEMENTAL DIGITAL CONTENT

Supplemental Figure S1. Top 30 covariates from random forests.

Supplemental Table S1. Multivariable predictors of waitlist death in the model that imputed unknown operative priority.



Observed vs. expected waitlist deaths by type of cardiac surgery. Legend: The error bars indicate 95% confidence intervals and were obtained through 200 bootstraps.

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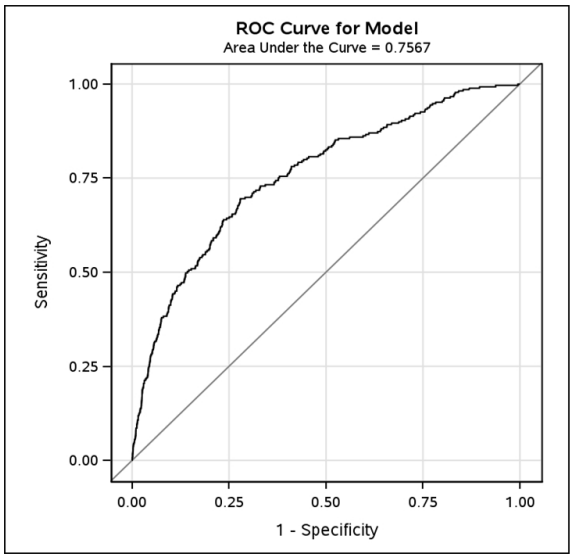


Receiver-operating characteristic curve of the CardiOttawa Waitlist Score model.

338x190mm (96 x 96 DPI)

Table 1. Baseline characteristics.

Variable	Dead (n=269)	Not Dead (n=111,997)	Total (n=112,266)	P-value
Demographics				
Age, Mean ± SD, y	70.3 ± 11.0	66.4 ± 10.9	66.4 ± 10.9	<0.001
Age, Median (IQR), y	71 (64-79)	67 (59-74)	67 (59-74)	<0.001
Female sex, No. (%)	80 (29.7)	28,574 (25.5)	28,654 (25.5)	0.112
BMI, Mean ± SD, kg/m^2	28.1 ± 5.7	28.8 ± 5.5	28.8 ± 5.5	0.052
BMI, Median (IQR), kg/m^2	27 (24-31)	28 (25-32)	28 (25-32)	0.017
Rural residence, No. (%)	42 (15.6)	17,181 (15.3)	17,223 (15.3)	0.901
Hospital type, No. (%)				0.816
Community	76 (28.3)	30,932 (27.6)	31,008 (27.6)	
Teaching	193 (71.7)	81,065 (72.4)	81,258 (72.4)	
Comorbidities				
Hypertension, No. (%)	233 (86.6)	94,413 (84.3)	94,646 (84.3)	0.297
Atrial fibrillation, No. (%)	54 (20.1)	19,898 (17.8)	19,952 (17.8)	0.323
Recent MI, No. (%)	81 (30.1)	27,295 (24.4)	27,376 (24.4)	0.029
CCS classification, No. (%)				<0.001
0	85 (31.6)	27,555 (24.6)	27,640 (24.6)	
1	25 (9.3)	10,812 (9.7)	10,837 (9.7)	
2	33 (12.3)	18,198 (16.2)	18,231 (16.2)	
3	29 (10.8)	16,158 (14.4)	16,187 (14.4)	
4	12 (4.5)	3,865 (3.5)	3,877 (3.5)	
Low-risk ACS	28 (10.4)	16,632 (14.9)	16,660 (14.8)	
Intermediate-risk ACS	35 (13.0)	14,477 (12.9)	14,512 (12.9)	
High-risk ACS	22 (8.2)	4,300 (3.8)	4,322 (3.8)	
LM or LM equivalent disease, No. (%)	105 (39.0)	46,651 (41.7)	46,756 (41.6)	0.384
Proximal LAD disease, No. (%)	97 (36.1)	43,483 (38.8)	43,580 (38.8)	0.353
Previous PCI, No. (%)	28 (10.4)	12,393 (11.1)	12,421 (11.1)	0.732
Left ventricular ejection fraction, No. (%)				<0.001
≥ 50%	135 (50.2)	78,679 (70.3)	78,814 (70.2)	
35-49%	77 (28.6)	22,667 (20.2)	22,744 (20.3)	
20-35%	47 (17.5)	8,989 (8.0)	9,036 (8.0)	
< 20%	10 (3.7)	1,662 (1.5)	1,672 (1.5)	
NYHA classification, No. (%)				<0.001
1	147 (54.6)	75,515 (67.4)	75,662 (67.4)	
2	57 (21.2)	17,821 (15.9)	17,878 (15.9)	
3	51 (19.0)	15,241 (13.6)	15,292 (13.6)	
4	14 (5.2)	3,420 (3.1)	3,434 (3.1)	

Heart failure, No. (%)	145 (53.9)	30,217 (27.0)	30,362 (27.0)	<0.001
Moderate-severe mitral regurgitation, No. (%)	38 (14.1)	9,830 (8.8)	9,868 (8.8)	0.002
Moderate-severe aortic regurgitation, No. (%)	15 (5.6)	3,567 (3.2)	3,582 (3.2)	0.026
Severe aortic stenosis, No. (%)	109 (40.5)	26,192 (23.4)	26,301 (23.4)	<0.001
Endocarditis, No. (%)				0.016
None	260 (96.7)	110,207 (98.4)	110,467 (98.4)	
Acute	8 (3.0)	1,260 (1.1)	1,268 (1.1)	
Subacute	<=5	530 (0.5)	531 (0.5)	
Cerebrovascular disease, No. (%)	41 (15.2)	11,407 (10.2)	11,448 (10.2)	0.006
Peripheral arterial disease, No. (%)	61 (22.7)	15,895 (14.2)	15,956 (14.2)	<0.001
Smoking status, No. (%)				0.345
Never	121 (45.0)	52,427 (46.8)	52,548 (46.8)	
Current	60 (22.3)	21,085 (18.8)	21,145 (18.8)	
Former	88 (32.7)	38,485 (34.4)	38,573 (34.4)	
COPD, No. (%)	100 (37.2)	26,035 (23.2)	26,135 (23.3)	
Diabetes, No. (%)	135 (50.2)	47,032 (42.0)	47,167 (42.0)	0.007
Dyslipidemia, No. (%)	168 (62.5)	74,354 (66.4)	74,522 (66.4)	0.172
GFR, Mean ± SD, mL/min/1.73m^2	69.4 ± 33.9	85.1 ± 34.8	85.0 ± 34.8	<0.001
GFR, Median (IQR), mL/min/1.73m^2	64 (47-88)	81 (61-105)	81 (61-105)	<0.001
Dialysis, No. (%)	34 (12.6)	3,093 (2.8)	3,127 (2.8)	<0.001
Anemia, No. (%)	37 (13.8)	9,304 (8.3)	9,341 (8.3)	0.001
Liver disease, No. (%)	9 (3.3)	1,551 (1.4)	1,560 (1.4)	0.006
Alcohol abuse, No. (%)	7 (2.6)	1,500 (1.3)	1,507 (1.3)	0.072
Dementia, No. (%)	6 (2.2)	1,475 (1.3)	1,481 (1.3)	0.19
Depression, No. (%)	7 (2.6)	1,425 (1.3)	1,432 (1.3)	0.052
Psychosis, No. (%)	<=5	214 (0.2)	217 (0.2)	<0.001
Primary cancer, No. (%)	17 (6.3)	5,611 (5.0)	5,628 (5.0)	0.325
Metastatic cancer, No. (%)	<=5	578 (0.5)	578 (0.5)	0.237
Operative characteristics				
Surgery type, No. (%)				<0.001
CABG	118 (43.9)	72,248 (64.5)	72,366 (64.5)	
Valve	81 (30.1)	24,380 (21.8)	24,461 (21.8)	
CABG + Valve	63 (23.4)	11,983 (10.7)	12,046 (10.7)	
Thoracic Aorta	7 (2.6)	3,386 (3.0)	3,393 (3.0)	
Redo-Sternotomy, No. (%)	19 (7.1)	3,315 (3.0)	3,334 (3.0)	<0.001
Cardiogenic Shock, No. (%)	<=5	221 (0.2)	223 (0.2)	0.044
Operative priority, No. (%)				<0.001
Unknown	67 (24.9)	13,004 (11.6)	13,071 (11.6)	

Emergent	18 (6.7)	3,460 (3.1)	3,478 (3.1)	
Urgent	90 (33.5)	31,244 (27.9)	31,334 (27.9)	
Semi-urgent	41 (15.2)	25,799 (23.0)	25,840 (23.0)	
Elective	53 (19.7)	38,490 (34.4)	38,543 (34.3)	
Recommend maximum wait time, Mean ± SD, d	23.3 ± 27.8	34.9 ± 31.3	34.9 ± 31.3	<0.001
Recommend maximum wait time, Median (IQR), d	14 (3-35)	22 (13-56)	22 (13-56)	<0.001
Adherence to recommended wait time, No. (%)	124 (46.1)	74,809 (66.8)	74,933 (66.7)	<0.001

Abbreviations: SD = standard deviation; IQR = interquartile range; BMI = body mass index; MI = myocardial infarction; CCS = Canadian Cardiovascular Society; ACS = acute coronary syndrome; LM = left main; LAD = left anterior descending; PCI = percutaneous coronary intervention; LVEF = left ventricular ejection fraction; NYHA = New York Heart Association; COPD = chronic obstructive pulmonary disease; GFR = glomerular filtration rate; CABG = coronary artery bypass grafting

Table 2. Multivariable predictors of waitlist death.

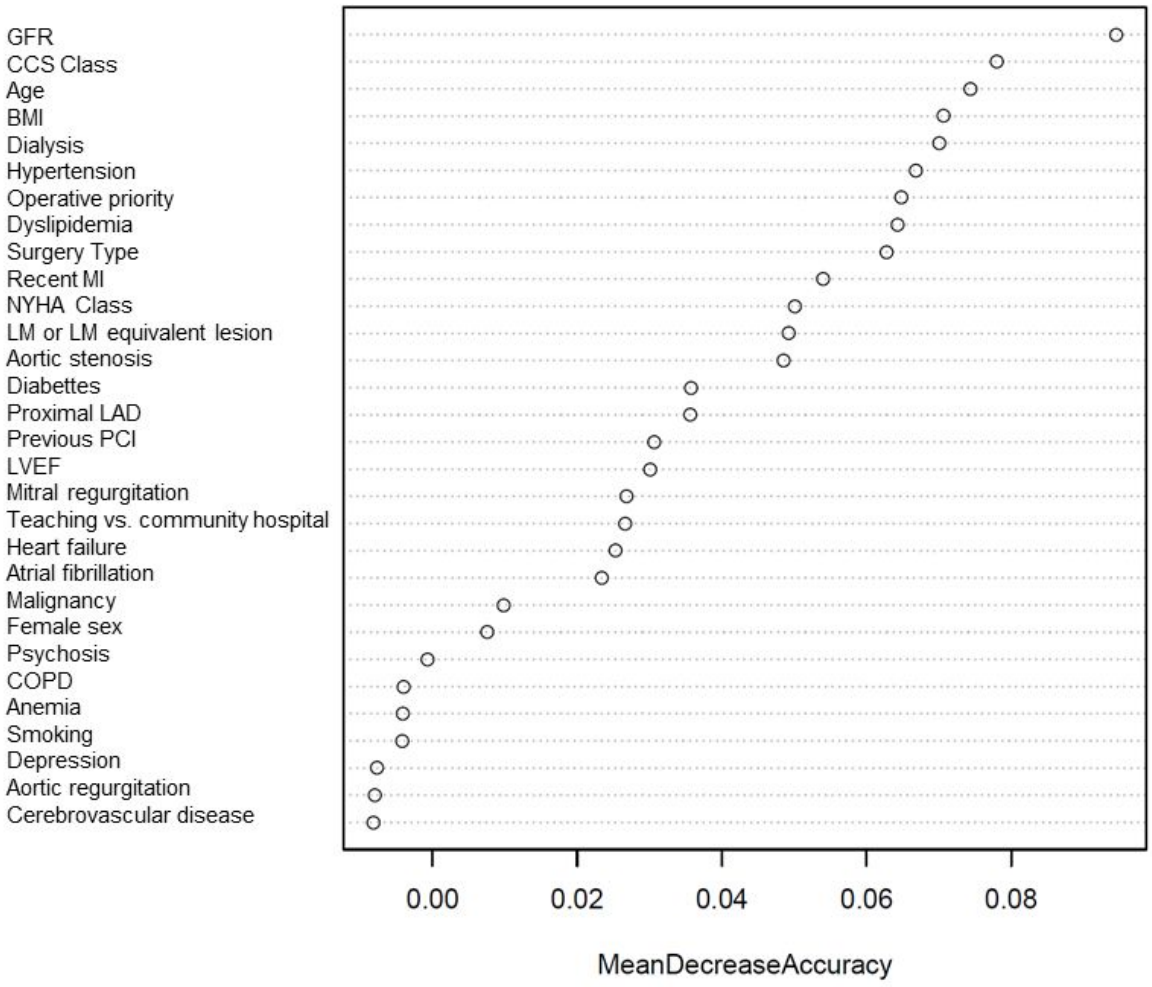
Variable	Model β-Coefficient	OR (95% CI)	Wald Chi-Square	P-value
Demographics				
Age, yr	0.0325	1.03 (1.02-1.05)	27.0617	<0.001
Female sex	0.0384	1.04 (0.79-1.36)	0.0774	0.781
Comorbidities				
CCS classification				
0	NA	Reference	Reference	NA
1	-0.0793	0.92 (0.59-1.46)	0.1159	0.734
2	-0.0537	0.95 (0.61-1.47)	0.0582	0.809
3	-0.0842	0.92 (0.58-1.46)	0.1280	0.721
4	0.3933	1.48 (0.78-2.82)	1.4389	0.230
Low-risk ACS	-0.1812	0.83 (0.51-1.35)	0.5365	0.464
Intermediate-risk ACS	0.0792	1.08 (0.66-1.77)	0.1002	0.752
High-risk ACS	0.4167	1.52 (0.74-3.11)	1.2934	0.255
LM or LM equivalent disease	0.2452	1.28 (0.98-1.76)	2.2699	0.132
Left ventricular ejection fraction				
≥ 50%	NA	Reference	Reference	NA
35-49%	0.6926	2.00 (1.49-2.69)	20.9352	<0.001
20-35%	0.9147	2.50 (1.72-3.62)	23.2995	<0.001
< 20%	1.0086	2.74 (1.39-5.43)	8.3881	0.004
Heart failure	0.5546	1.74 (1.31-2.31)	14.8925	<0.001
Atrial fibrillation	-0.5502	0.58 (0.42-0.79)	11.6325	<0.001
Dialysis	1.3167	3.73 (2.56-5.44)	47.0533	<0.001
Psychosis	1.6878	5.41 (1.70-17.19)	8.1826	0.004
Operative characteristics				
Surgery type				
CABG	NA	Reference	Reference	NA
Valve	0.7432	2.10 (1.33-3.32)	10.1776	0.001
CABG + Valve	0.8396	2.32 (1.58-3.40)	18.2858	<0.001
Thoracic Aorta	0.0213	1.02 (0.42-2.49)	0.0022	0.963
Operative priority				
Unknown	0.7940	2.21 (1.42-3.45)	12.2517	<0.001
Emergent	0.3014	1.35 (0.60-3.04)	0.5335	0.465
Urgent	-0.00965	0.99 (0.65-1.50)	0.0021	0.964
Semi-urgent	-0.0391	0.96 (0.62-1.49)	0.0309	0.861
Elective	NA	Reference	Reference	NA

Abbreviations: OR = odds ratio; CI = confidence interval; CCS = Canadian Cardiovascular Society; LM = left main coronary artery; CABG = coronary artery bypass grafting

Table 3. Observed versus predicted number of patients who died while awaiting cardiac surgery. The 95% confidence intervals were obtained through 200 bootstraps with replacement.

Risk Quintile	Total	Observed		Predicted		OR (95% CI)
		No. Events	Rate, % (95% CI)	No. Events	Rate, % (95% CI)	
1 (Low likelihood)	22455	13	0.058 (0.029-0.094)	13.09	0.058 (0.058-0.059)	Reference
2 (Low-moderate)	22450	24	0.11 (0.069-0.15)	21.46	0.096 (0.095-0.096)	1.85 (0.94-3.63)
3 (Moderate)	22474	29	0.13 (0.080-0.17)	32.86	0.15 (0.15-0.15)	2.23 (1.16-4.29)
4 (Moderate-high)	22437	52	0.23 (0.18-0.29)	52.78	0.24 (0.23-0.24)	4.01 (2.18-7.37)
5 (High)	22450	151	0.67 (0.56-0.76)	148.83	0.66 (0.65-0.67)	11.69 (6.63-20.61)

Supplemental Figure S1. Top 30 covariates from random forests.



Supplemental Table S1. Multivariable predictors of waitlist death in the model that imputed unknown operative priority.

Variable	Model β-Coefficient	Wald Chi-Square	P-value
Demographics			
Age, yr	0.0309	24.2855	<.0001
Female sex	0.0421	0.0932	0.7602
Comorbidities			
CCS classification			
0	NA	NA	NA
1	-0.0688	0.0877	0.7671
2	-0.0660	0.0887	0.7659
3	-0.1050	0.2008	0.6541
4	0.4066	1.5561	0.2122
Low-risk ACS	-0.2022	0.6820	0.4089
Intermediate-risk ACS	0.0600	0.0663	0.7968
High-risk ACS	0.6361	5.5885	0.0181
LM or LM equivalent disease	0.2378	2.3020	0.1292
Left ventricular ejection fraction			
≥ 50%	NA	NA	NA
35-49%	0.7009	21.4972	<.0001
20-35%	0.9267	24.5732	<.0001
< 20%	1.0397	9.2154	0.0024
Heart failure	0.5625	15.4619	<.0001
Atrial fibrillation	-0.5342	11.0024	0.0009
Dialysis	1.3167	47.0915	<.0001
Psychosis	1.6746	8.0561	0.0045
Operative characteristics			
Surgery type			
CABG	NA	NA	NA
Valve	0.9931	22.7598	<.0001
CABG + Valve	1.0354	34.4080	<.0001
Thoracic Aorta	0.7872	3.5428	0.0598

Abbreviations: OR = odds ratio; CI = confidence interval; CCS = Canadian Cardiovascular Society; LM = left main coronary artery; CABG = coronary artery bypass grafting