Derivation and Validation of Pragmatic Clinical Models to Predict Hospital Length of Stay After Cardiac Surgery in Ontario, Canada

Short Title: Predicting Length of Stay after Cardiac Surgery

Alexandra Fottinger, BM BCh; Anan Bader Eddeen, MSc; Douglas S. Lee, MD, PhD; Graham Woodward, MSc; Louise Y. Sun, MD, SM

From the Division of Cardiac Anesthesiology, University of Ottawa Heart Institute, Ontario, Canada (AF, LYS); ICES, Ontario, Canada (ABE, DSL, LYS); Peter Munk Cardiac Centre, University Health Network, University of Toronto, Ontario, Canada (DSL); CorHealth Ontario (GW) and the School of Epidemiology and Public Health, University of Ottawa, Ontario, Canada (LYS).

Address for Correspondence:

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

Clinician Scientist and Associate Professor

University of Ottawa Heart Institute

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

Phone: 1 613 696 7381 Email: lsun@ottawaheart.ca

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Conception and Design: LYS

Data acquisition and analysis: ABE, LYS

Interpretation of data: AF, ABE, LYS

Drafting of the manuscript: AF, LYS

Critical revision and final approval: AF, ABE, DSL, GW, LYS

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ABSTRACT

Background: Cardiac surgery is resource intensive and often requires considerable length of stay (LOS). To facilitate evidence-based resource planning, we derived and validated a set of clinical models to predict postoperative hospital LOS.

Methods: We used linked, population-level databases with information on all Ontario residents. Included were patients ≥18 years of age who underwent coronary artery bypass grafting, valvular, or thoracic aorta surgeries between October 2008 and September 2019. The primary outcome was hospital LOS. The models were derived on patients who had surgery before September 30, 2016 and validated on those after that date. To address the rightward skew in LOS data and to identify top-tier resource users, we used logistic regression to derive a model to predict the likelihood of LOS being >98th percentile (≥35 days). We then used gamma regression in the remainder to predict the actual LOS in days. We used backward stepwise variable selection for both models.

Results: Among 105,193 patients, 2,422 (2.3%) had LOS of ≥35 days. The median LOS was 46 (IQR, 37-66) days for those with LOS in the top 2 percentiles and 6 (5-8) days for those without. The c-statistic was 0.92 for the prolonged LOS model and the mean absolute error was 2.4 days for the model that predicted actual LOS.

Interpretation: We derived and validated a set of clinical models to identify top-tier resource users and predict actual LOS with excellent accuracy. Our models could be used to benchmark quality, rationally allocate resources and support patient-centered operative decision-making.

Key Words: cardiac surgery, length of stay, hospitalization, access to care, capacity planning, patient-centered research

INTRODUCTION

Around the world, approximately 2 million cardiac surgeries are performed each year.[1,2] Cardiac surgery is resource intensive. It carries a higher burden of complications, requires intensive postoperative monitoring, and often longer hospital length of stay (LOS) as compared to noncardiac surgery[3]. With steady improvements in surgical technique and perioperative care, cardiac surgery is increasingly being offered to frail and complex patients with higher resource needs[4,5]. Organizations' drive for operational efficiency and competing capacity needs in the era of COVID-19 makes evidence-based triaging and resource allocation, founded on real-world data, an urgent priority. Prediction of intensive care unit (ICU) LOS after cardiac surgery[6–8] is important but does not fully reflect the extent of resources needed. Nonetheless, few models are available to predict postoperative LOS in hospital. Although existing models include those from the Society of Thoracic Surgeons (STS) and the EuroSCORE datasets [9–11], they were developed to predict perioperative mortality and end organ morbidity and were only later validated in single center datasets for the purpose of predicting prolonged LOS. To better inform health resource planning, we derived and externally validated clinical models using population-based data to identify top-tier resource users and to predict actual hospital LOS after cardiac surgery.

METHODS

The dataset from this study is held securely in coded form at ICES (formerly the Institute 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.[12]

Design and Population

We conducted a population-based, retrospective cohort study of adult patients ≥ 18 years of age, who underwent coronary artery bypass grafting (CABG), aortic, mitral or tricuspid valve, or thoracic aorta surgery in Ontario, Canada between October 1, 2008 and September 30, 2019. For patients with multiple cardiac procedures during the study period, only the index procedure was included in the analyses. Ontario is the most populous province in Canada, with about 14.6 million residents and is ethnically diverse[1,3].

Data Source

We used the clinical registry of CorHealth Ontario and population-level administrative healthcare databases from ICES. ICES is an independent, non-profit research institute whose legal status under Ontario's health information privacy law allows it to collect and analyze health care and demographic data, without consent, for health system evaluation and improvement. Datasets were linked deterministically using confidential identifiers and analyzed at ICES. ICES holds multiple population-based health databases of Ontario residents. CorHealth Ontario maintains a prospective registry of all patients who undergo invasive cardiac procedures in Ontario and regularly undergoes selected chart audits and core laboratory validation.[12]

We linked the CorHealth Ontario registry (patient and procedural details) with the Canadian Institute for Health Information Discharge Abstract Database (comorbidities, hospital admissions and in-hospital procedures), the Ontario Health Insurance Plan database (physician service claims) and the Registered Persons Database (vital statistics). These administrative databases have been validated for many outcomes, exposures, and comorbidities, including heart failure, chronic obstructive pulmonary disease, asthma, hypertension, and diabetes.[14–17]

Potential covariates considered in the analyses are described in **Table 1** and included demographic, physiological, anatomical and comorbidity data, as well as procedure-specific information (operative priority status, redo sternotomy, type of surgery, and surgery duration). We obtained data on height, weight, operative priority, and information pertaining to LVEF, valvular disease and coronary anatomy from the CorHealth Ontario registry. In addition, we identified comorbidities from the CorHealth Ontario registry which we supplemented with data from the Discharge Abstract Database and the Ontario Health Insurance Plan database using International Classification of Diseases 10th Revision (ICD-10-CA) codes[18] within five years prior to surgery, according to validated algorithms.[14,16,19,20]

Outcome

The primary outcome was hospital LOS. As LOS data is invariably right-skewed with extreme values in those with prolonged stay,[21,22] we derived two separate models: the first (binary outcome model) to identify the top-tier resource users (i.e., LOS exceeding the 98th percentile value of ≥ 35 days), and the other (continuous outcome model) to predict the actual LOS in days in the remainder of the cohort.

Statistical Analysis

We compared continuous variables using a 2-sample *t*-test or Wilcoxon rank sum test where appropriate, and categorical variables using a chi-square test.

Missing Data

Left ventricular ejection fraction (LVEF) was missing in 3 582 (3.4%), rurality status in 87 (0.08%), income quintile in 272 (0.26%), GFR in 4 671 (4.4%), BMI in 5 583 (5.3%), surgery duration in 1 317 (1.2%) and operative priority 12 060 (11.5%) patients. We imputed these missing values once within the SAS "proc MI" framework, where they were predicted drawing on all candidate covariates using predictive mean matching for continuous variables and logistic regression for categorical variables.[23]

Model Development and Validation

We split the cohort temporally into a derivation and validation datasets, such that the cohort who underwent cardiac surgery before September 30, 2016 was used to derive the models and the remainder of the cohort was used to externally validate these models. We predicted prolonged hospital LOS using logistic regression and actual hospital LOS using gamma regression. For each of the models, we selected predictor variables using a backward stepwise algorithm with a significance threshold of $P < 0.1$ for entry and $P < 0.05$ for retention in the model.[24] For continuous variables, we examined their association with the outcome using cubic splines. Most of these variables were entered into the models as continuous values, while body mass index (BMI) violated the linearity assumption and was entered as a spline term.

Model Evaluation

The discrimination of the binary outcome model was evaluated using the c-statistic and its calibration was assessed using the Brier score,[25] as well as plots of observed versus predicted rates within deciles of predicted risk in the validation cohort. The performance of the continuous outcome model was assessed using the mean absolute error (MAE), as well as plots of mean observed versus predicted LOS in days within each decile of observed LOS in the validation cohort.

We performed the analysis using SAS 9.4 (SAS Institute, Cary, NC) and defined statistical significance by a two-sided *P*-value of < 0.05.

RESULTS

Patient Characteristics

Among 105 193 patients, 2 422 (2.3%) had prolonged hospital LOS of ≥ 35 days. The median LOS was 46 (IQR, 37-66) days for those with prolonged LOS and 6 (5-8) for the remainder of the cohort. Patient characteristics were notably different between groups (**Table 1**). Patients with prolonged hospital LOS were older, more frail, and more likely to be female, have lower income levels and to present urgently and emergently for complex procedures (CABG + valve(s), multiple valves and thoracic aorta surgery) at teaching hospitals. They are also more likely to have a higher multimorbidity burden, reduced LVEF, and longer surgical durations.

Predictors of Length of Stay

The binary model for prolonged LOS consisted of 16 variables (**Table 2**) and the continuous model consisted of 28 variables (**Table 3**). The characteristics common to both models are procedure type and duration, age, rural residence, BMI, frailty, Canadian Cardiovascular Society and New York Heart Association classification status, LVEF, glomerular filtration rate, valvular disease, diabetes requiring treatment, anemia, cerebrovascular disease, malignancy, and depression. The continuous outcome model additionally included sex, presenting at a community hospital, operative priority, atrial fibrillation, endocarditis, peripheral arterial disease, COPD, pulmonary circulatory disease, alcoholism, dementia, and psychosis.

Model Performance

Binary outcome model

The c-statistic was 0.92 in both derivation and validation datasets, demonstrating excellent discrimination. The model was well calibrated, with a Brier score of 0.016 and the observed and predicted risks of prolonged LOS being very similar across all probability deciles in the calibration dataset (**Figure 1**).

Continuous outcome model

The continuous model had a MAE of 2.3 days in the derivation dataset. The MAE was 2.4 in the validation dataset, indicating good predictive accuracy. The calibration plot in **Figure 2** shows that the mean observed and predicted hospital LOS within each LOS decile were nearly identical in the validation cohort.

INTERPRETATION

Operative decision-making may be enhanced by objective tools to more efficiently allocate resources in a patient-centered manner. Traditional statistical models are dated; they are limited to the prediction of prolonged LOS of varying durations and fail to predict actual LOS[26–29]. While the latter is beginning to be explored using machine learning techniques in isolated CABG patients, it is based on small, single-center datasets and lack generalizability in the broader healthcare setting[30,31]. Our models were pragmatically designed for operational capacity planning and were derived and validated in a large and representative population to overcomes these limitations. In this population, the risk-adjusted average hospital LOS for the 2011 – 2016 fiscal years were reported as 7.85 days for isolated CABG, 9.26 days for isolated AVR, and 12.07 days for CABG/AVR[32]. Of note, this report had trimmed hospital LOS at the 99th percentile to remove extreme observations, much like the methodology employed in our analysis to isolate top-tier resource users who are at the highest risk of complications, worsening frailty, functional decline and loss of personal freedom and independence after surgery[12,33–37]. The ability to identify those at risk for extremely prolonged LOS allows for better decision-making from the perspectives of the healthcare system as well as the individual patient. As the system level, this ability, coupled with actual LOS prediction, will facilitate data-driven clinical scheduling to increase throughput, facilitate targeted interventions such as prehabilitation, Enhanced Recovery After Surgery, and early referral to continuing care facilities. As prolonged LOS has also been implicated with increased healthcare cost[9] and disability after discharge,[12,35,36,38,39] our predictive models will inform effective provider-patient discussions and encourage patient-centered operative decision-making.

Notably, our binary outcome model demonstrated excellent performance with a c-statistic of 0.92 and outperforms existing models. Comparatively, the EuroScore had a c-statistic of 0.71 (0.69-0.72) for predicting prolonged hospital LOS (> 12 days) when validated in a monocentric setting[11], and the STS model had a c-statistic of 0.716-0.732 for predicting short hospital LOS of ≦ 5 days and 0.739-0.796 for predicting prolonged stay of > 5 days, depending on the type of surgery performed.[40] It should also be noted that these models rely on designated staff for data collection, which constitutes further healthcare resource demands and is not feasible at all centers.

Our continuous outcome model was able to predict LOS with an error margin of 2 days, which is accepted in a publicly funded healthcare ecosystem given LOS could be influenced by the availability of post-discharge continuing care facilities and home-based caregivers rather than medical indications alone. Importantly, our ability to predict actual LOS enables precision-based hospital capacity planning, as well as quality benchmarking and incentivized allocation of healthcare funding. Incorporation of the model into tools such as the province-wide CorHealth information system could also help individual providers to understand bed requirements at the time of intervention, allowing for more accurate resource planning.

Many risk factors from our LOS models are consistent with those published in the literature[9,41]. We were additionally able to incorporate frailty as a defining element of perioperative outcomes and recovery[42,43], as well as anemia, dementia, psychosis, hospital type, and a variety of sociodemographic factors to ensure that all patient groups are equally represented. The variables included in our models are routinely collected and readily available to facilitate their adoption at most institutions.

Strengths and Limitations

Notable strengths of our models include their generalizability across the scope of cardiac surgery in a large and representative population, as well as their relevance to clinicians, policy makers and patients. Limitations include the lack of certain detailed physiologic measures such as the brain natriuretic peptide in the databases used, as well as their limited application in those who undergo minimally invasive cardiac procedures.

CONCLUSIONS

We derived and validated a set of clinical prediction models to identify top-tier resource users (hospital LOS $\geq$ 35 days) and actual LOS after cardiac surgery with excellent accuracy. The importance of these models lies in their potential to support medical resource planning and patient-centered decision-making. Care, outcomes, and patient satisfaction may be substantially improved if clinical judgment is supported by objective quantification in the planning of care. Being based on an unbiased population-based sample, these models could be combined with established ICU LOS[7] and waitlist[44] management tools to provide evidence-based triaging decision support, to conserve system capacity, enhance operational efficiency, as well as to benchmark performance.

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FIGURE LEGENDS

Figure 1. Calibration plot of observed vs. predicted risk of extremely prolonged postoperative hospital length of stay of ≥ 35 days, according to deciles of expected rate.

Figure 2. Calibration plot of observed vs. predicted average lengths of hospital stay in days, within each decile of expected length of stay.

TABLES

Table 1. Baseline characteristics of patients by length of hospital stay.

	Length of stay <35 d	Length of stay ≥35 d	*P*-Value
Demographics			
Age, Mean +/- SD, y	66.26 (10.76)	70.64 (11.34)	<0.001
Age, Median (IQR), y	67 (59-74)	73 (64-79)	<0.001
Female sex, n (%)	25 151 (24.5%)	832 (34.4%)	<0.001
BMI, Mean +/- SD, kg/m^2	28.85 (5.74)	29.25 (6.81)	0.001
BMI, Median (IQR), kg/m^2	28 (25-32)	28 (25-33)	0.504
Rural residence, n (%)	15 853 (15.4%)	318 (13.1%)	0.002
Hospital type, n (%)			<0.001
Community	29 328 (28.5%)	553 (22.8%)	
Teaching	73 443 (71.5%)	1 869 (77.2%)	
Income Quintile			<0.001
1 (lowest)	19 540 (19.0%)	564 (23.3%)	
2	20 992 (20.4%)	546 (22.5%)	
3	21 122 (20.6%)	487 (20.1%)	
4	20 754 (20.2%)	446 (18.4%)	
5 (highest)	20 363 (19.8%)	379 (15.6%)	
Comorbidities			
Hypertension, n (%)	87 359 (85.0%)	2 188 (90.3%)	<0.001
Atrial fibrillation, n (%)	6 905 (6.7%)	397 (16.4%)	<0.001
Recent MI. n (%)	23 547 (22.9%)	637 (26.3%)	<0.001
CCS classification, n (%)			<0.001
0	21 997 (21.4%)	703 (29.0%)	
1	9 733 (9.5%)	183 (7.6%)	
2	17 026 (16.6%)	164 (6.8%)	
3	15 106 (14.7%)	246 (10.2%)	
4	3 584 (3.5%)	99 (4.1%)	
Low-risk ACS	15 530 (15.1%)	265 (10.9%)	
Intermediate-risk ACS	13 343 (13.0%)	331 (13.7%)	
High-risk ACS	3 883 (3.8%)	155 (6.4%)	
Emergent	2 569 (2.5%)	276 (11.4%)	

Left ventricular ejection fraction, n (%)			<0.001
≥ 50%	72 714 (70.8%)	1 464 (60.4%)	
35-49%	20 860 (20.3%)	552 (22.8%)	
20-35%	7 847 (7.6%)	321 (13.3%)	
<20%	1 350 (1.3%)	85 (3.5%)	
NYHA classification, n (%)			<0.001
1	72 445 (70.5%)	1 273 (52.6%)	
2	15 396 (15.0%)	350 (14.5%)	
3	12 153 (11.8%)	532 (22.0%)	
4	2 777 (2.7%)	267 (11.0%)	
Heart failure, n (%)	26 585 (25.9%)	1 455 (60.1%)	<0.001
Valve disease, n (%)	29 813 (29.0%)	1 184 (48.9%)	<0.001
Endocarditis, n (%)			<0.001
None	101 436 (98.7%)	2 293 (94.7%)	
Acute	938 (0.9%)	112 (4.6%)	
Subacute	397 (0.4%)	17 (0.7%)	
Cerebrovascular disease, n (%)	9 948 (9.7%)	385 (15.9%)	<0.001
Peripheral arterial disease, n (%)	13 647 (13.3%)	502 (20.7%)	<0.001
Smoking status, n (%)			<0.001
None	47 527 (46.2%)	1 185 (48.9%)	
Current	19 889 (19.4%)	459 (19.0%)	
Former	35 355 (34.4%)	778 (32.1%)	
COPD, n (%)	23 756 (23.1%)	833 (34.4%)	<0.001
Diabetes, n (%)	29 816 (29.0%)	833 (34.4%)	<0.001
GFR, Mean +/- SD, ml/min/1.73m^2	74.05 (21.42)	58.78 (25.42)	<0.001
GFR, Median (IQR), ml/min/1.73m^2	77 (61-90)	58 (41-79)	<0.001
Dialysis, n (%)	2 070 (2.0%)	196 (8.1%)	<0.001
Anemia, n (%)	10 170 (9.9%)	714 (29.5%)	<0.001
Liver disease, n (%)	977 (1.0%)	58 (2.4%)	<0.001
Dementia, n (%)	1 296 (1.3%)	86 (3.6%)	<0.001
Depression, n (%)	1 359 (1.3%)	132 (5.5%)	<0.001
Psychosis, n (%)	205 (0.2%)	9 (0.4%)	0.0631
Malignancy, n (%)	5 207 (5.1%)	174 (7.2%)	<0.001
Paraplegia, n (%)	294 (0.3%)	22 (0.9%)	<0.001
Pulmonary circulatory disease, n (%)	2 279 (2.2%)	181 (7.5%)	<0.001
Hospital frailty risk score *			<0.001

High-risk, n (%)	1 166 (1.1%)	557 (23.0%)	
Intermediate-risk, n (%)	16 474 (16.0%)	1 511 (62.4%)	
Low-risk, n (%)	85 131 (82.8%)	354 (14.6%)	
Operative characteristics			
Surgery type, n (%)			<0.001
CABG	67 703 (65.9%)	839 (34.6%)	
Single valve	14 964 (14.6%)	383 (15.8%)	
Multiple valves	1 745 (1.7%)	118 (4.9%)	
CABG + single valve	10 034 (9.8%)	463 (19.1%)	
CABG + multiple valves	690 (0.7%)	70 (2.9%)	
Thoracic aorta	7 635 (7.4%)	549 (22.7%)	
Redo-sternotomy, n (%)	2 800 (2.7%)	148 (6.1%)	<0.001
Cardiogenic shock, n (%)	427 (0.4%)	46 (1.9%)	<0.001
Operative priority, n (%)			<0.001
Emergent	5,379 (5.2%)	392 (16.2%)	
Urgent	31 487 (30.6%)	1 074 (44.3%)	
Semi-urgent	26 072 (25.4%)	397 (16.4%)	
Elective	39 833 (38.8%)	559 (23.1%)	
Surgery duration, mean (SD), min	279.59 (80.67)	350.27 (126.11)	<0.001
Surgery duration, median (IQR), min	268 (225-319)	327 (265-403)	<0.001
Post-operative characteristics			
Length of stay, mean (SD), d	7.47 (4.19)	58.02 (36.35)	<0.001
Length of stay, IQR (SD), d	6 (5-8)	46 (37-66)	<0.001

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

* Gilbert et al. (2018)

Table 2. Multivariable predictors of prolonged hospital length of stay of ≥ 35 days.

Variable	β-coefficient	Adjusted Odds Ratio (95% CI)	P Value
Demographics			
Age	0.0205	1.02 (1.02-1.03)	<0.001
BMI, per 1 kg/m^2	-0.0380	0.96 (0.94-0.98)	0.0005
Rural	-0.1848	0.83 (0.71-0.97)	0.0166
Co-morbidities			
CCS classification			
0	N/A	Reference	N/A
1	-0.1967	0.82 (0.67-1.01)	0.0603
2	-0.3822	0.68 (0.55-0.85)	0.0006
3	0.0114	1.01 (0.84-1.22)	0.9064
4	0.1511	1.16 (0.89-1.53)	0.2751
Low risk ACS	-0.2074	0.81 (0.67-0.99)	0.0357
Intermediate risk ACS	-0.0392	0.96 (0.8-1.16)	0.6854
High risk ACS	0.4073	1.50 (1.18-1.91)	0.0009
Emergent	0.803	2.23 (1.79-2.78)	<.0001
LVEF			
≥ 50%	N/A	Reference	N/A
35-49%	0.1052	1.11 (0.98-1.26)	0.1093
20-35%	0.0506	1.05 (0.89-1.24)	0.5551
<20%	0.5591	1.75 (1.31-2.34)	0.0002
Heart failure	0.3731	1.45 (1.29-1.64)	<0.001
CVD	-0.2409	0.79 (0.68-0.91)	0.0009
Diabetes (treated)	0.1497	1.16 (1.04-1.3)	0.0105
eGFR	-0.00390	1.00 (0.99-1.00)	0.0007
Anemia	-0.2997	0.74 (0.65-0.84)	<0.001
Depression	0.3184	1.37 (1.08-1.75)	0.0100
Malignancy	-0.2093	0.81 (0.66-0.99)	0.0399
Valvular disease	-0.2247	0.80 (0.68-0.94)	0.0078
Hospital frailty risk score *			
High-risk	4.2723	71.69 (59.01-87.09)	<0.001
Intermediate-risk	2.6876	14.70 (12.75-16.94)	<0.001
Low-risk	N/A	Reference	N/A
Operative Characteristics			
Surgery type			
CABG	N/A	Reference	N/A

Single valve	0.7583	2.13 (1.71-2.66)	<0.001
Multivalve	0.8855	2.42 (1.77-3.33)	<0.001
CABG + single valve	0.6876	1.99 (1.63-2.43)	<0.001
CABG + multivalve	1.0779	2.94 (2.06-4.19)	<0.001
Thoracic aorta	0.9391	2.56 (2.14-3.06)	<0.001
Surgery duration, per 10 min	0.00393	1.040 (1.035-1.045)	<0.001

Abbreviations: BMI = body mass index; CCS = Canadian Cardiovascular Society; LVEF = left ventricular ejection fraction; CVD = cerebrovascular disease; e GFR = estimated glomerular filtration rate; CABG = coronary artery bypass grafting.

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Table 3. Multivariable predictors of a continuous model describing actual hospital length of stay in days.

Variable	β-coefficient	Rate Ratio (95% CI)	P Value
Demographics			
Age	0.007500	1.01 (1.01-1.01)	<0.001
Sex, female	0.077071	1.08 (1.07-1.09)	<0.001
BMI, per 1 kg/m^2	-0.006353	0.994 (0.993-0.995)	<0.001
Rural	-0.038102	0.96 (0.96-0.97)	<0.001
Community hospital	0.032697	1.03 (1.03-1.04)	<0.001
Co-morbidities			
Atrial fibrillation	0.023919	1.02 (1.01-1.04)	<0.001
CCS			
0	N/A	Reference	N/A
1	-0.013390	0.99 (0.98-1.00)	0.0185
2	-0.011821	0.99 (0.98-1.00)	0.0228
3	0.007720	1.01 (1.00-1.02)	0.1461
4	0.023578	1.02 (1.01-1.04)	0.0061
Low risk ACS	0.004400	1.00 (0.99-1.02)	0.4320
Intermediate risk ACS	0.039144	1.04 (1.03-1.05)	<.001
High risk ACS	0.038623	1.04 (1.02-1.06)	0.0013
Emergent	0.135774	1.15 (1.12-1.18)	<.001
LVEF			
≥ 50%	N/A	Reference	N/A
35-49%	0.014921	1.02 (1.01-1.02)	<0.001
20-35%	0.045719	1.05 (1.04-1.06)	<0.001
<20%	0.115012	1.12 (1.10-1.15)	<0.001
NHYA class			
1	N/A	Reference	N/A
2	0.011695	1.01 (1.00-1.02)	0.0111
3	0.026415	1.03 (1.02-1.04)	<0.001
4	0.060932	1.06 (1.04-1.08)	<0.001
Heart Failure	0.072425	1.08 (1.07-1.08)	<0.001
Endocarditis			
Acute	0.199950	1.22 (1.18-1.26)	<0.001
Subacute	0.025726	1.03 (0.98-1.07)	0.2623
CVD	0.027025	1.03 (1.02-1.04)	<0.001

PAD	0.018385	1.02 (1.01-1.03)	<0.001
COPD	0.037918	1.04 (1.03-1.05)	<0.001
Diabetes (treated)	0.031403	1.03 (1.03-1.04)	<0.001
eGFR	-0.001126	1.00 (1.00-1.00)	<0.001
Anemia	0.028545	1.03 (1.02-1.04)	<0.001
Alcohol use	0.033998	1.03 (1.01-1.06)	0.0041
Dementia	0.046793	1.05 (1.02-1.07)	0.0002
Depression	0.079752	1.08 (1.06-1.11)	<0.001
Psychosis	0.134990	1.14 (1.08-1.21)	<0.001
Pulmonary circulatory disease	0.078703	1.08 (1.06-1.10)	<0.001
Valvular disease	-0.014392	0.99 (0.98-1.00)	0.0082
Hospital frailty risk score *			
High-risk	0.510984	1.67 (1.62-1.71)	<0.001
Intermediate-risk	0.340613	1.41 (1.39-1.42)	<0.001
Low-risk	N/A	Reference	N/A
Operative Characteristics			
Surgery type			
CABG	N/A	Reference	N/A
Single valve	0.125445	1.13 (1.12-1.15)	<0.001
Multiple valves	0.224929	1.25 (1.22-1.28)	<0.001
CABG + Valve	0.131862	1.14 (1.13-1.16)	<0.001
CABG + Multivalve	0.174254	1.19 (1.15-1.23)	<0.001
Thoracic aorta	0.141773	1.15 (1.14-1.17)	<0.001
Redo sternotomy	-0.031499	0.97 (0.95-0.98)	<0.001
Surgery duration, per 10 min	0.000996	1.010 (1.0096-1.0104)	<0.001
Surgical priority			
Emergent	0.047870	1.05 (1.03-1.07)	<0.001
Urgent	0.002829	1.00 (0.99-1.01)	0.5711
Semi-urgent	0.004538	1.00 (1.00-1.01)	0.2277
Elective	N/A	Reference	N/A

Abbreviations: BMI = body mass index; CCS = Canadian Cardiovascular Society; LVEF = left ventricular ejection fraction; NYHA = New York Heart Association; CVD = cerebrovascular disease; PAD = peripheral arterial disease; COPD = chronic obstructive pulmonary disease; eGFR = estimated glomerular filtration rate; CABG = coronary artery bypass grafting.

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FIGURES

Figure 1. Calibration plot of observed vs. predicted risk of extremely prolonged postoperative hospital length of stay of ≥ 35 days, according to deciles of expected rate.

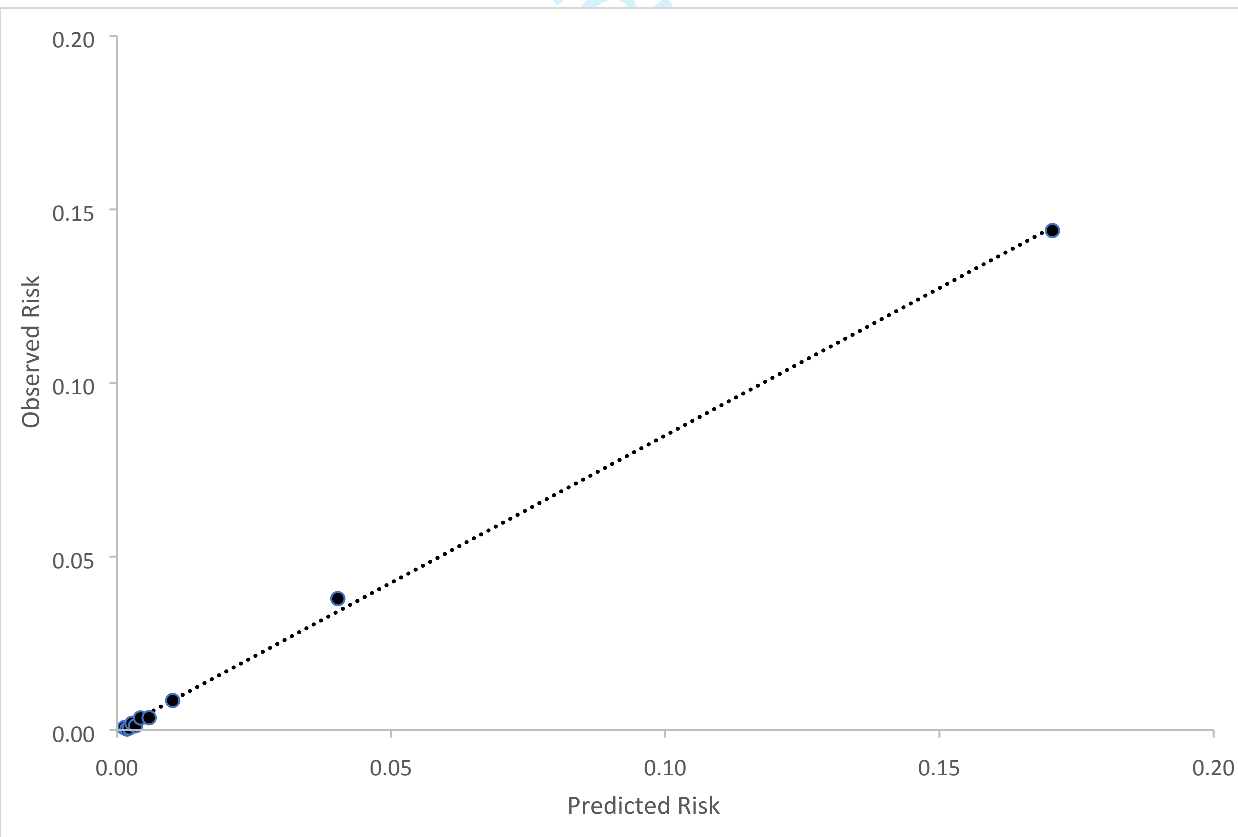

Figure 2. Calibration plot of observed vs. predicted average lengths of hospital stay in days, within each decile of expected length of stay.