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Analysis of risk factors and establishment of a risk prediction model for cardiothoracic surgical intensive care unit readmission after heart valve surgery in China: A single-center study

Si Li [a], Bai-yun Tang [a], Bao Zhang [a], Cui-ping Wang [a], Wen-bo Zhang [a], Song Yang [a], Jia-bin Chen [b,*]

[a] *Department of Cardiothoracic Surgical Intensive Care Unit, First Affiliated Hospital, Sun Yat-sen University, Guangzhou 510080, China*
[b] *Inpatient Department, Guangdong Province Hospital for Occupational Disease Prevention and Treatment, 68 Haikang St., Xingang Rd. W., Guangzhou 510300, China*

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A B S T R A C T

Background: Valvular heart disease is one of the most frequent and challenging heart diseases worldwide. The incidence of complications and cardiothoracic surgical intensive care unit (CSICU) readmission after cardiac valve surgery is high. Because CSICU readmission is costly and adversely impacts the quality life, reducing the risk of CSICU readmission has become one of the main focuses of health care.

Objective: To explore the risk factors for CSICU readmission and to establish a risk prediction model for CSICU readmission in heart valve surgical patients.

Methods: A total of 1216 patients who had undergone cardiac valvular surgery between January 2016 and August 2017 at the First Affiliated Hospital of Sun Yat-sen University were assigned as the development and validation data sets. Data from 824 patients in the development data set were retrospectively analyzed to identify potential risk factors with univariate analysis. Multivariate logistic regression was used to determine the independent risk factors of CSICU readmission, which served as the basis for our prediction model. The calibration and discrimination of the model were assessed by the Hosmer–Lemeshow (H–L) test and the area under the receiver operating characteristic (ROC) curve, respectively.

Results: Six preoperative variables (age $\geq$ 65, previous chronic lung disease, prior cardiac surgery, left ventricular ejection fraction (LVEF) $\leq$ 40%, 40% < LVEF $\leq$ 50%, and New York Heart Association (NYHA) classification III/IV), two intraoperative variables (multiple valve repair/replacement and cardiopulmonary bypass time $\geq$ 180 min), and five postoperative variables (cardiac arrest, acute respiratory distress syndrome, pneumonia, deep sternal wound infection, and renal failure) were independent risk factors of CSICU readmission. Our risk prediction model, which was established based on the above-mentioned risk factors, had robust discrimination and calibration in both the development and validation data sets.

Conclusion: The prediction model established in our study is a simple, objective, and accurate scoring system, which can be used to predict the risk of CSICU readmission and assist researchers with designing intervention strategies to prevent CSICU readmission.

Introduction

Valvular heart disease is one of the most common heart diseases. Studies have reported that the number of patients undergoing cardiac valve surgery is increasing.[1] Nearly 275,000 cardiac valve operations are performed annually worldwide, and the mortality of patients undergoing cardiac valve surgery is high,[2] especially among patients who require readmission to the intensive care unit (ICU) for significant worsening of their clinical conditions. ICU readmission after cardiac surgical procedures, including valve surgery, occurs in 2.3% to 8.7% of patients.[3–6] In addition, ICU readmission is associated with the poor quality of life, increased economic burden, and the consumption of valuable medical

Abbreviation list: CSICU, cardiothoracic surgical intensive care unit; LVEF, left ventricular ejection fraction; NYHA, New York Heart Association; CPB, cardiopulmonary bypass; ROC, receiver operating characteristic; H–L, Hosmer–Lemeshow X^2 test; AUC, area under the curve; CABG, coronary artery bypass; SD, standard deviation; BMI, body mass index; IQR, interquartile range; SE, standard error; OR, odds ratio; RBC, red blood cell; ARDS, acute respiratory distress syndrome; BMI, body mass index; ACC, aortic cross-clamp; ICU, intensive care unit; SPSS, statistical package for the social sciences; IABP, intra-aortic balloon pump; INR, international normalized ratio.

* Corresponding author.
E-mail address: jbcemail@126.com (J.-b. Chen).

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resources.[3,7,8] Therefore, uncovering the potential risk factors for CSICU readmission after heart valve surgery could lead to the development of early intervention strategies, which may reduce CSICU readmission and hospital costs.

At present, some risk prediction models are used clinically in developed countries to predict postoperative mortality, length of ICU stay, and readmission rates after external or cardiac surgery.[9–11] However, there has been limited empirical testing of prediction models for ICU readmission after heart valve surgery. In recent years, several reports have suggested that different risk prediction models should be established on the basis of various risk factors, including different disease causes, lesion sites, and types of cardiac surgery.[12,13] Meanwhile, previous studies have shown that risk prediction models used in Western countries are inappropriate for Chinese and some other Asian population.[14–17] Considering that genetics, the heterogeneity in racial backgrounds, education, access to medical facilities and the epidemiology of heart valve disease in Chinese population may be different from those of western developed countries,[18] it is imperative to establish a suitable risk prediction model for Chinese population.

In this study, we sought to identify risk factors for CSICU readmission after heart valve surgery, which may provide a basis for the rational evaluation of the prognosis of patients in our hospital. Furthermore, we explored potential risk prediction models for CSICU readmission after heart valve surgery in our institution, and hope that this model may be used in China as well.

Methods

Study population and databases

Our study was approved by the Ethics Committee of our hospital. The medical records from a total of 1280 consecutive adult patients who had undergone cardiac valvular surgery between January 2016 and August 2017 at the First Affiliated Hospital of Sun Yat-sen University in Guangzhou, China, were registered in this study. Patients with any of the following conditions were excluded from this study (1) congenital valvular disease (= 38), (2) deceased after surgery or during the initial ICU stay (= 16), and (3) unavailable clinical data (= 10). After applying the exclusion and inclusion criteria, the data of a total of 1216 patients were collected retrospectively from medical records.

Preoperative variables included age, sex, smoking, body mass index (BMI), hypertension, history of stroke, dyslipidemia, history of chronic lung disease, previous myocardial infarction, active endocarditis, previous cardiac surgery, left ventricular ejection fraction (LVEF), the New York Heart Association (NYHA) classification III/IV, red blood cell (RBC) count and serum creatinine. Intraoperative variables included positive inotropic drug use, multiple valve repair/replacement, cardiopulmonary bypass (CPB) time, aortic cross-clamp (ACC) time, and intraoperative RBC transfusion. Postoperative variables included the length of the initial ICU stays, cardiac arrest, atrial fibrillation, acute respiratory distress syndrome (ARDS), history of pneumonia, deep sternal wound infection, renal failure, and gastrointestinal bleeding. All of the above postoperative variables and complications occurred prior to discharge from the initial ICU and were identified using Society of Thoracic Surgeons database data definitions.[19] In the eligible study cohort, 824 patients who had undergone heart valve surgery between January 2016 and January 2017 were assigned as the development data set while 392 patients from February 2017 assigned as validation data set. In the development data set, we compared the characteristics of the patients who were readmitted and not readmitted to CSICU.

CSICU discharge criteria and readmission criteria

The decision to transfer patients from the CSICU to the general cardiac surgery ward was jointly made by the CSICU and ward physicians according to the patient's individual health status. The general CSICU discharge criteria include absence of cognitive impairment, no serious organ dysfunction, no sign of perioperative myocardial infarction, stable vital signs, spontaneous breathing and acceptable blood gas analysis index, stable hemodynamics, and no evidence of severe infections or sepsis. “CSICU readmission” is defined as a patient's second CSICU admission due to the significant worsening of their clinical conditions. The decision to readmit patients to the CSICU was made by ward physicians based on clinical judgement. “Cause of readmission” is defined as the primary complications observed during the first 48 h of a CSICU stay after readmission.

Statistical analysis

Statistical analyses were performed by using SPSS 20.0 (IBM, Armonk, NY, USA). Continuous normally distributed data ware summarized with means and standard deviations (SD). Medians with the interquartile range (IQR), where appropriate, were used for continuous non-normally distributed data. Descriptive statistics were presented as frequencies with percentages for categorical variables. Differences in categorical variables were assessed with the chi-square test or the Fisher's exact test, and differences in continuous variables were examined with the Student's *t*-test or the Mann–Whitney *u*-test. The variables with an univariate significant threshold of $p < 0.05$ were considered for inclusion within a conditional multivariate logistic regression model after assessment for multicollinearity. The risk factors were determined by forward step analysis, and the risk score model was established according to the corresponding regression coefficient. A probability (p) value < 0.05 was considered statistically significant.

The final risk prediction model was evaluated in terms of discrimination and calibration in the development and validation data sets. Discrimination was used as a measure of ability of the model to discriminate between readmitted and non-readmitted patients. In addition, discrimination was tested by the C-index evaluated by calculating the area under the ROC curve. A C-index $>$ 0.7 indicates a reasonable discriminative power of the model. Calibration was evaluated by assessing the degree of correspondence between the estimated probabilities produced by the model and the actual observations. It was assessed by Hosmer–Lemeshow (H–L) test, and a well-calibrated model was expected to have a p-value > 0.05.

Results

The final study population consisted of 1216 patients who undergone heart valve surgery procedures between January 2016 and August 2017 at our hospital. Demographic and clinical characteristics of the study population are listed in Tables 1 and 2. There was no significant difference between clinical characteristics in the development and validation data sets. Fifty-two (6.3%) and 28 (7.1%) patients in the development and validation data sets were readmitted to the CSICU after discharge, respectively. Among the readmitted patients, 71 (88.7%) were readmitted once, 7 (8.8%) were readmitted twice, and 2 (2.5%) were readmitted three or more times. In addition, ten patients were readmitted to the CSICU within 48 h after CSICU discharge. The most common cause of readmission to the CSICU was cardiac complications (= 31, 38.8%), followed by respiratory complications (= 22, 27.5%), serious infections (= 10, 12.5%), renal failure (= 8, 10.0%), digestive complications (= 4, 5.0%),

Table 1
Clinical and demogprahic characteristics of patients in the development and validation data sets.

Characteristic	Overall (= 1216)	Development (= 824)	Validation (= 392)	*p*-value
Preoperative variables				
Age, mean (SD), years	58.7 ± 8.2	58.5 ± 8.0	59.1 ± 8.6	0.28
Male, n, %	585 (48.1%)	391 (47.5%)	194 (49.5%)	0.51
Smoking, %	206 (16.9%)	144 (17.5%)	62 (15.8%)	0.47
BMI, mean (SD), kg/m^2	27.87 ± 5.69	27.89 ± 5.67	27.85 ± 5.73	0.91
Hypertension, n, %	229 (18.8%)	152 (18.4%)	77 (19.6%)	0.62
Previous stroke, n, %	59 (4.9%)	43(5.2%)	16 (4.1%)	0.39
Dyslipidemia, n, %	46 (3.8%)	30 (3.6%)	16 (4.1%)	0.71
Previous chronic lung disease, n, %	265 (21.8%)	182 (22.1%)	83 (21.2%)	0.72
Previous myocardial infarction, n, %	40 (3.3%)	25 (3.0%)	15 (3.8%)	0.47
Active endocarditis, n, %	72 (5.9%)	47 (5.7%)	25 (6.4%)	0.63
Previous cardiac surgery, n, %	36 (3.0%)	24 (2.9%)	12 (3.1%)	0.89
LVEF, mean (SD), %	60.2 ± 10.7	59.8 ± 10.6	60.9 ± 10.8	0.10
NYHA III/IV, n, %	298 (24.6%)	212 (25.7%)	86 (21.9%)	0.15
RBC count, mean (SD), g/L	137.6 ± 18.4	137.7 ± 18.5	137.3 ± 18.3	0.76
Serum creatinine, mean (SD), μmol/L	81.92 ± 21.47	81.99 ± 21.25	81.77 ± 21.95	0.87
Intraoperative variables				
Positive inotropic drug, n, %	768 (63.2%)	531 (64.4%)	237 (60.5%)	0.18
multiple valve repair/replacement, n, %	537 (44.2%)	363 (44.1%)	174 (44.4%)	0.91
CPB time, median (P25-P75), min	152 (121,187)	154 (122,190)	148 (118,182)	0.38
ACC time, mean (SD), min	75.4 ± 26.9	75.3 ± 27.2	75.5 ± 26.2	0.91
Intraoperative RBC transfusion, n, %	458 (37.7%)	310 (37.6%)	148 (37.8%)	0.96
Postoperative variables				
Length of initial ICU stay, median (P25-P75), h	44 (20,64)	42 (19,63)	47 (20,66)	0.42
Cardiac arrest, n, %	22 (3.6%)	29 (3.5%)	15 (3.8%)	0.79
Atrial fibrillation, n, %	339 (27.9%)	226 (27.4%)	113 (28.8%)	0.61
ARDS, n, %	58 (4.8%)	39 (4.7%)	19 (4.8%)	0.93
Pneumonia, n, %	170 (14.0%)	111 (13.5%)	59 (15.1%)	0.46
Deep sternal wound infection, n, %	23 (1.9%)	15 (1.8%)	8 (2.0%)	0.79
Renal failure, n, %	90 (7.4%)	62 (7.5%)	28 (7.1%)	0.81
Gastrointestinal bleeding, n, %	83 (6.8%)	57 (6.9%)	26 (6.6%)	0.85

The data are presented as mean ± SD or median (P25-P75). The enumeration data are presented as n (%). Differences between the development and validation data sets were tested using the Student's *t*-test or the Mann–Whitney *u*-test for continuous variables and the chi-square test or Fisher's exact test for categorical variables.

neurologic complications, and other factors (= 5, 6.3%). The in-hospital mortality of patients with CSICU readmission was 22.5%, significantly higher than the 1.8% mortality rate of the patients without readmission ($p < 0.01$).

The distribution of valve procedures for the development data set is shown in Table 3. In the development data set, the univariate analysis revealed significant differences in sixteen variables between the patients who were readmitted and not readmitted to CSICU (Table 2). The sixteen variables included age, history of chronic lung disease, previous myocardial infarction, previous cardiac surgery, LVEF, NYHA III/IV, RBC count, testing positive for inotropic drugs, multiple valve repair/replacement, CPB time, the length of the initial ICU stay, cardiac arrest, acute respiratory distress syndrome, pneumonia, deep sternal wound infection, and renal failure.

To evaluate predictors of readmission to the CSICU, we considered variables that had significant univariate associations with this outcome within a conditional multivariate logistic regression analysis, which was carried out using the forward stepwise analysis with an entry threshold of $p \le 0.05$ and a removal threshold of $p > 0.1$. The multivariate logistic regression model revealed that thirteen variables, including age $\ge$ 65 (risk score = 5), previous chronic lung disease (risk score = 3), previous cardiac surgery (risk score = 6), 40 % $<$ LVEF $\le$ 50% (risk score = 5), LVEF $\le$ 40% (risk score = 9), NYHA III/IV (risk score = 6), multiple valve repair/replacement (risk score = 3), CPB time $\ge$ 180 min (risk score = 9), cardiac arrest (risk score = 14), acute respiratory distress syndrome (risk score = 13), pneumonia (risk score = 11), deep sternal wound infection (risk score = 11), and renal failure (risk score = 16), were independent risk factors associated with CSICU readmission ($R^2 = 0.775$, $p < 0.05$; Table 4).

Based on the results of the multivariate logistic regression analysis, the simplified logistic regression model to be established in this study was:

$$Prob\ (event) = \frac{1}{1 + \exp{-}[\beta_0 + (10\beta_1 X_1 + 10\beta_2 X_2 + \cdots 10\beta_i X_i)/10]},$$

where *Prob* refers to the probability of being readmitted to the CSICU. For the convenience of the clinical application of this model, $10\beta_i$ was defined as the independent risk score of the risk factor. Then, the above equation can be simplified to:

$$Prob\ (event) = \frac{1}{1 + \exp{-}[-3.426 + \mathrm{TotalScores}/10]}.$$

The C-index of our model was 0.886 and 0.881 in the development and validation data sets, respectively, suggesting that the risk prediction model exhibited reasonable discriminatory abilities (Fig. 1). Meanwhile, the risk prediction model demonstrated good agreement between the observed and predicted readmission to the CSICU for patients after heart valve surgery in both the development and validation data sets with H–L *p*-values of 0.303 and 0.286, respectively (Fig. 2). Predicted probability of readmission for our model in validation data set was 8.51%. The observed/expected (O/E) ratio of readmission rate in validation data set was 0.84.

Finally, according to our risk prediction model equation, a CSICU readmission prediction model nomogram was drawn for the convenience of clinical application. The model nomogram showed a positive correlation between the risk score and the probability of CSICU readmission. As the risk score increased, the probability of readmission to the CSICU also increased (Fig. 3).

Table 2
Clinical and demographic characteristics of patients with and without a CSICU readmission in the development data set.

Characteristic	No readmission (= 772)	Readmission (= 52)	*p*-value
Preoperative variables			
Age, mean (SD), years	58.15 ± 7.86	64.00 ± 8.64	<0.001
Male, *n*, %	364 (47.1%)	27 (51.9%)	0.50
Smoking, %	132 (17.1%)	12 (19.2%)	0.27
BMI, mean (SD), kg/m^2	27.96 ± 5.62	26.81±6.33	0.16
Hypertension, *n*, %	141 (18.3%)	11 (21.2%)	0.60
Previous stroke, *n*, %	38 (4.9%)	5 (9.6%)	0.14
Dyslipidemia, *n*, %	26 (3.4%)	4 (7.7%)	0.11
Previous chronic lung disease, *n*, %	163 (21.1%)	19 (36.5%)	0.009
Previous myocardial infarction, *n*, %	20 (2.6%)	5 (9.6%)	0.017
Active endocarditis, *n*, %	43 (5.6%)	4 (7.7%)	0.53
Previous cardiac surgery, *n*, %	15 (1.9%)	9 (17.3%)	<0.001
LVEF, mean (SD), %	60.2 ± 10.6	55.2 ± 8.5	<0.001
NYHA III/IV, *n*, %	190 (24.6%)	22 (42.3%)	0.005
RBC count, mean (SD), g/L	138.1 ± 18.4	131.7±20.1	0.017
Serum creatinine, mean (SD), μmol/L	81.72 ± 21.28	85.87 ± 20.68	0.17
Intraoperative variables			
Positive inotropic drug, *n*, %	488(63.2%)	43 (82.7%)	0.005
multiple valve repair/replacement, *n*, %	329 (42.6%)	34 (65.4%)	0.001
CPB time, median (P25-P75), min	141 (115,171)	176 (139,242)	<0.001
ACC time, mean (SD), min	74.9 ± 27.1	81.7 ± 28.3	0.08
Intraoperative RBC transfusion, *n*, %	286 (37.0%)	24 (46.2%)	0.19
Postoperative variables			
Length of initial ICU stay, median (P25-P75), h	36 (18,59)	53 (22,73)	0.021
Cardiac arrest, *n*, %	22 (2.8%)	7 (13.5%)	<0.001
Atrial fibrillation, *n*, %	209 (27.1%)	17 (32.7%)	0.38
ARDS, *n*, %	30 (3.9%)	9 (17.3%)	<0.001
Pneumonia, *n*, %	93 (12.0%)	18 (34.6%)	<0.001
Deep sternal wound infection, *n*, %	10 (1.3%)	5 (9.6%)	0.002
Renal failure, *n*, %	46 (6.0%)	16 (30.8%)	<0.001
Gastrointestinal bleeding, *n*, %	52 (6.7%)	5 (9.6%)	0.40

The measurement data is presented as mean ± SD or median (P25-P75). The enumeration data is presented as *n* (%). Differences in categorical variables were tested by using the chi-square test or Fisher's exact test and differences in continuous variables were tested using the Student's *t*-test or the Mann–Whitney *u*-test.

Discussion

Valvular heart disease is one of the most frequently-occurred and challenging heart diseases to treat. Many heart valve surgeries are being performed annually worldwide. Even in developed regions, such as the United Kingdom, United States, and Europe, the associated short-term mortality of heart valve surgery is between 4% and 8%, which is far greater than that of CABG surgery.[1,20,21] In China, the situation is similar, but valvular heart diseases are typically caused by rheumatic heart disease. While the rate of rheumatic heart disease has decreased in recent years,[22] multiple valve surgery for rheumatic heart disease still accounts for approximately 40% of all heart valve surgeries in China.[23] Meanwhile, the prevalence of degenerative valvular diseases is climbing as the population ages.[24] While recent advances in surgical techniques have significantly reduced the mortality rate for elderly patients after valvular surgery to levels comparable to that of younger patients, the incidence of complications and ICU readmission among elderly patients are still high.[11] For instance, previous studies have reported that ICU readmissions occurred in up to 7.8% of cardiac surgery patients and that in-hospital mortality rates ranged from 11 to 31% in readmitted patients,[4,6,25,26] which were consistent with our findings of 6.6% and 22.5%, respectively. Given the impact of ICU readmission on mortality rates, postoperative quality of life, and hospital expenditures, an understanding of the risk factors associated with CSICU readmission is crucial for effective prevention. Thus, an efficient and reliable post-cardiac valve surgery ICU readmission prediction model is necessary for assessing the related risk factors.

Currently, several influential risk prediction score systems, including the EuroSCORE, are used to predict the risks of heart valve surgery and postoperative mortality after cardiac surgery in developed countries.[27,28] However, Parolari *et al.* showed that the accuracy of the EuroSCORE model was poor in predicting risks in cardiac valve surgery.[29] Wang *et al.* also pointed out that all four risk score prediction models currently being used in clinical practice, including EuroSCORE II, Ambler score, NYC score, and STS score, were not suitable for prediction on Chinese patients undergoing multiple valve surgery,[18] which was likely because of the different design rationales, criteria, and purposes. For instance, we found that the most significant risk of CSICU readmission was postoperative complications according to our study, suggesting that the EuroSCORE, which was designed for coronary heart disease based on preoperative clinical indices, was not fit for revealing the risk factors of CSICU readmission.

Considering the accuracy of prediction models, Jin et al. have suggested that logistic models should be used in all risk

Table 3
Distribution of valve procedures for the development data set.

Procedures	Number (*n*)	Concomitant CABG (%)	Proportion (%)
Single valve	461	29 (6.29%)	55.95%
Aortic valve	189	13 (6.88%)	22.94%
Mitral valve	210	14 (6.67%)	25.49%
Tricuspid valve	60	2 (3.33%)	7.28%
Pulmonic valve	2	0 (0%)	0.24%
Multiple valve	363	11 (3.03%)	44.05%
Aortic and Mitral valve	58	3 (5.17%)	7.04%
Aortic and Tricuspid valve	5	1 (20%)	0.61%
Aortic and Pulmonic valve	4	0 (0%)	0.49%
Mitral and Tricuspid valve	172	5 (2.91%)	20.87%
Tricuspid and Pulmonic valve	2	0 (0%)	0.24%
Aortic, Mitral, and Tricuspid valve	118	2 (1.69%)	14.32%
Aortic, Mitral, and Pulmonic valve	2	0 (0%)	0.24%
Mitral, Tricuspid, and Pulmonic valve	2	0 (0%)	0.24%

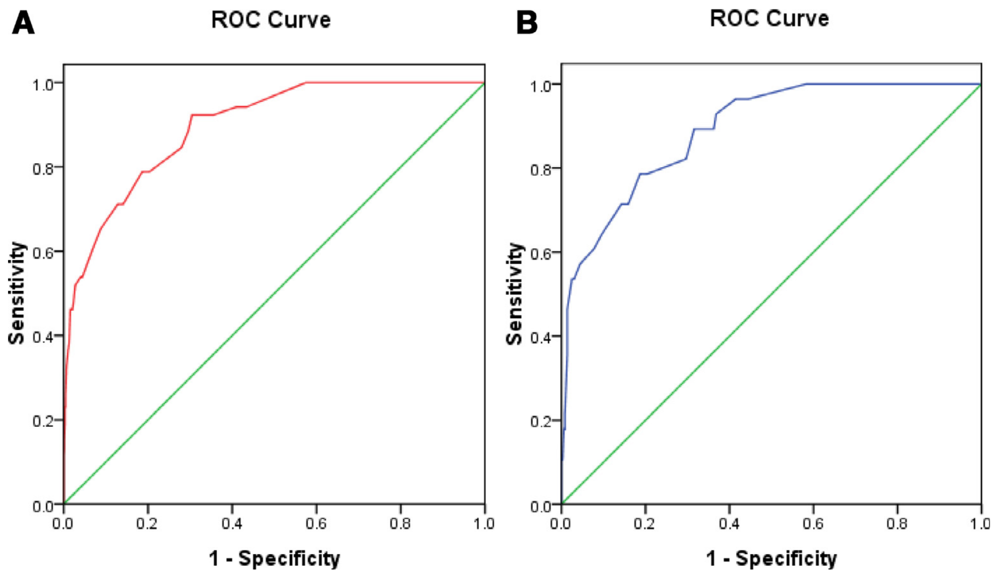

Fig. 1. Receiver operating characteristic (ROC) curve of the risk predicted model for valve surgery in the development (A) and validation datasets (B). Model discrimination was evaluated by calculating the area under ROC curve (AUC c-index), which was used as a measure of how well the model discriminated between readmitted and non-readmitted patients. The C-index values range from 0.5 (no ability to discriminate) to 1.0 (full ability to discriminate). A C-index of more than 0.7 indicated a reasonable discriminative power of the model, and a C-index greater than 0.8 indicated a strong discriminative power of the model.

prediction score systems.[30] However, the conventional logistic model is complex, so it is not convenient for clinical application. Therefore, we sought to create a risk prediction score system based on a simplified logistic model, which could identify these patients with high risk of CSICU readmission better and fit for the clinical application.

Previously, factors including age, LVEF, lung disease, surgical procedure (multiple valve repair/replacement), and postoperative renal failure were found to be associated with ICU readmission after cardiac surgery.[3,4,6,26] Consistent with these findings, our final model included six preoperative variables, two intraoperative variables, and five postoperative complications, which covered the above mentioned clinical manifestations. We also noted that the major reasons of CSICU readmission were cardiovascular and respiratory complications, the latter of which was in agreement with a previous report stating that respiratory complications were independent factors of readmission.[7] LVEF and NYHA classification are indicators of preoperative cardiac function. The results of this study suggest that the cardiac function of patients with preoperative LVEF $\leq$ 50% may have been more severely impaired. Patients with poor cardiac function are often readmitted to ICU for serious cardiovascular complication if there is poor monitoring and nursing care. Multivariate analysis also shows that LVEF and NYHA classification are risk factors of readmission.

In the present study, we identified CPB time and infection as risk factors for CSICU readmission. While the mortality rates for related patients have dropped in recent years due to advances in CPB techniques and antibiotic therapies,[31,32] long-term CPB and infections remain critical risk factors resulting in postoperative complications and increased mortality. Patients with these risk factors need more peri- and post-operative care to avoid ICU readmission after valvular surgery.

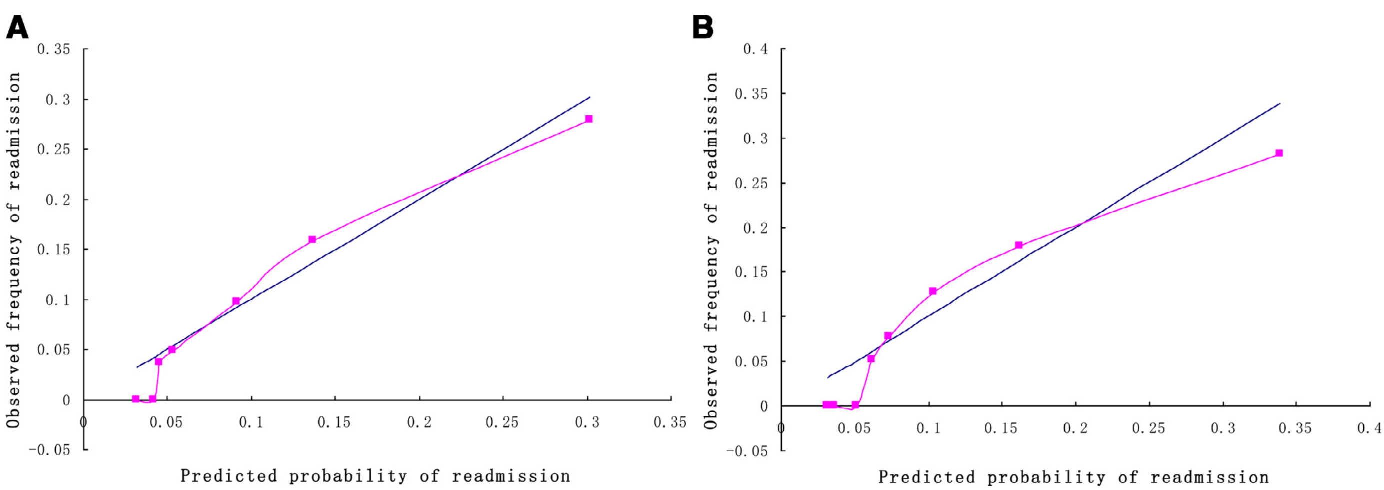

Fig. 2. Calibration plot of the risk predicted model in the development (A) and validation datasets (B). Both data cohorts were equally divided into ten groups according to patient risk scores, respectively. The dots on the calibration plot indicated the observed frequency and predicted the probability of readmission for the corresponding groups in the cohort. This plot shows the model performance of the risk predicted model for the entire cohort. The risk prediction model demonstrates good calibration in predicting readmission to the CSICU for patients after heart valve surgery in both the development and validation data sets with H–L p-values of 0.303 and 0.286, respectively. The calibration plots are close to a straight line, exceeding 45 degrees.

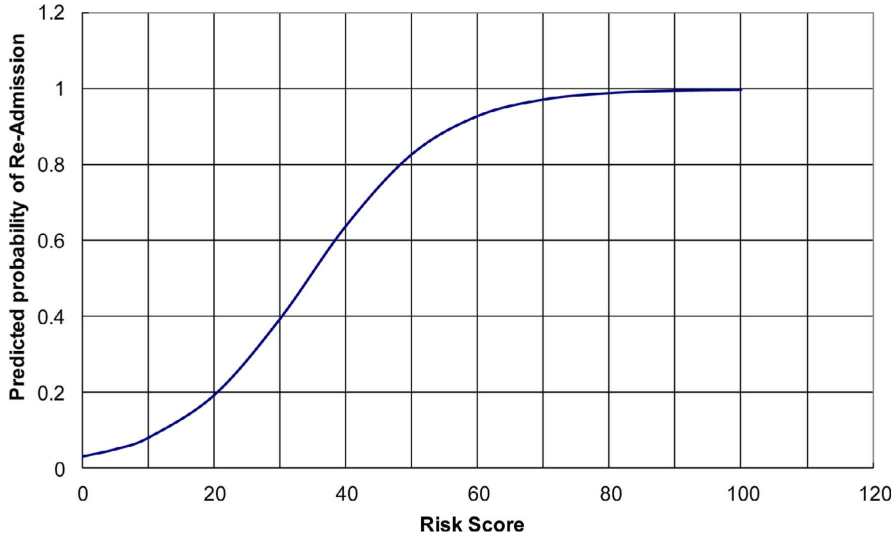

Fig. 3. The CSICU readmission prediction model nomogram for heart valve surgery. This figure is for the convenience of the clinical application based on our CSICU readmission prediction model equation.

We found that the highest risk factor was renal failure, defined as a threefold increase in creatinine, serum creatinine > 4 mg/dL with an acute rise of at least 0.5 mg/dL, or newly onset dialysis. According to our CSICU readmission prediction model nomogram, postoperative renal failure alone would increase the CSICU readmission rate to 13.8%. As acute kidney injury occurred in 20–40% of patients after cardiac surgery,[33] clinicians should increase their awareness that how to prevent renal failure during the early postoperative period. In addition, postoperative cardiac arrest was also identified as an independent risk factor of CSICU readmission in our study. To the best of our knowledge, this is the first study showed the correlation between cardiac arrest and CSICU readmission rates, despite postoperative cardiac arrest being associated with longer hospital stays and higher mortality.[34–36]

Our CSICU readmission prediction model demonstrated excellent discrimination and calibration. Compared with the conventional logistic model,[37] our model had some major improvements. First, the regression coefficient increased by a factor of ten, and then integrated as an independent risk score of the risk factor. Also, a readmission prediction model nomogram was drawn for reaching the corresponding probability of readmission quickly according to the score. Through these improved measures, our model maintained not only its original accuracy but also simple application at the bedside to evaluate the individual risk of patients.

Having identified the risk factors for CSICU readmission through our model, we planned to start a implementation of more rigorous measures to reduce the readmission rates. For instance, clinical measures for patients with postoperative pneumonia included clinical monitoring, enhanced respiratory function training, and early use of antibiotics. For patients with low LVEF, the application of preoperative cardiac stimulants and preoperative or intraoperative intra-aortic balloon pump (IABP) are recommended. Considering that postoperative excessive bleeding is more common for patients with previous cardiac surgery, it is essential to improve pre-operative coagulation function, stop the intraoperative bleeding actively and make constant monitoring of postoperative international normalized ratio (INR). In brief, in order to prevent postoperative complications and reduce CSICU readmission, attention should be paid to patient-specific optimization of nursing care and surgical care as well as peri-operative health education for patients. We expect that the risk prediction model may be applied directly after hospitalization. Patients' data should be collected through the postoperative period, and the probability of readmission will be used in helping clinicians determine discharge potential. Overall, our model enables the identification of a

Table 4
Risk factors independently predicting CSICU readmission and corresponding risk scores.

Variable	Regression coefficient	SE	Risk score	Wald X^2	OR	*p*-value
Constant	-3.426	0.928		13.629	0.033	<0.001
Age ≥ 65 [a]	0.462	0.135	5	11.712	1.587	0.001
Previous chronic lung disease	0.285	0.128	3	4.958	1.330	0.026
Previous cardiac surgery	0.636	0.253	6	6.319	1.889	0.012
40% < LVEF ≤ 50% [b]	0.532	0.167	5	10.148	1.702	0.001
LVEF ≤ 40% [b]	0.891	0.403	9	4.888	2.438	0.027
NYHA III/IV	0.648	0.249	6	6.773	1.912	0.009
Multiple valve repair/replacement	0.317	0.130	3	5.946	1.373	0.015
CPB ≥ 180 min [c]	0.916	0.261	9	12.317	2.499	<0.001
Cardiac arrest	1.422	0.397	14	12.830	4.145	<0.001
ARDS	1.281	0.416	13	9.482	3.600	0.002
Pneumonia	1.118	0.348	11	10.321	3.059	0.001
Deep sternal wound infection	1.079	0.379	11	8.105	2.942	0.004
Renal failure	1.587	0.532	16	8.899	4.889	0.003

[a] Reference age < 65.
[b] Reference LVEF > 50%
[c] Reference CPB < 180 min.

sizable cohort of patients who may be at high risk for readmission. For these patients, additional treatments or conservative recommendations may be cost-effective and beneficial.[38] Of course, the robust performance of our model was also due to the inclusion of a comprehensive set of clinical variables, surgical variables, and complications spanning the entire perioperative period to the first CSICU discharge.

A newly developed valve surgery approach, transcatheter aortic valve replacement (TVAR), is increasingly popular with intermediate to high surgical risks.[39] While TVAR significantly reduced patient mortality and cardiovascular adverse events,[40] the procedure is still associated with some major vascular complications.[41] Our risk prediction model was established based on open surgery, and it will be of great interest to include TVAR in our model in the future.

Our study had several limitations that merit consideration. First, this was a retrospective study performed in a single center with a limited number of patients. Therefore, the generalizability of our prediction model should be further corroborated in a multi-center large cohort studies in the future. Second, no patient's clinical data after their CSICU discharge were collected in this study. However, the discrimination and calibration of our model were excellent with the available variables.

Conclusions

Based on an observational dataset of patients undergoing valvular surgery in our hospital, we developed and validated a prediction model for readmission after CSICU discharge by using a comprehensive set of clinical variables spanning the entire perioperative period. The model demonstrated excellent discrimination and calibration. Our prediction model is a simple, objective, and accurate scoring system which can predict CSICU readmission and make therapeutic interventions aiming at its prevention. However, due to the limitations of our study, the model needs further validation and optimization using a large external data set in the future.

Conflicts of interest

None.

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