Machine learning models to predict red blood cell transfusion in patients undergoing mitral valve surgery

Shun Liu[1#], Rong Zhou[2#], Xing-Qiu Xia[3], He Ren[3], Le-Ye Wang[4,5], Rui-Rui Sang[2], Mi Jiang[2], Chun-Chen Yang[2], Huan Liu[1], Lai Wei[1], Rui-Ming Rong[2]

[1]Department of Cardiovascular Surgery, Zhongshan Hospital, Shanghai Cardiovascular Institution, Fudan University, Shanghai, China; [2]Department of Transfusion, Zhongshan Hospital, Fudan University, Shanghai, China; [3]Beijing HealSci Technology Co., Ltd., Beijing, China; [4]Key Laboratory of High Confidence Software Technologies (Peking University), Ministry of Education, Beijing, China; [5]Department of Computer Science and Technology, Peking University, Beijing, China

Contributions: (I) Conception and design: All authors; (II) Administrative support: RM Rong; (III) Provision of study materials or patients: L Wei, RM Rong; (IV) Collection and assembly of data: S Liu, R Zhou, RR Sang, M Jiang, CC Yang; (V) Data analysis and interpretation: XQ Xia, H Ren, LY Wang; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

[#]These authors contributed equally to this work.

Correspondence to: Lai Wei. 1609 Xietu Road, Building 16, Shanghai, China. Email: wl_heartsurgeon@126.com; Rui-Ming Rong. 180 Fenglin Road, Building 1, Shanghai, China. Email: rongruiming1969@163.com.

Background: Red blood cell (RBC) transfusion therapy has been widely used in surgery, and has yielded excellent treatment outcomes. However, in some instances, the demand for RBC transfusion is assessed by doctors based on their experience. In this study, we use machine learning models to predict the need for RBC transfusion during mitral valve surgery to guide the surgeon's assessment of the patient's need for intraoperative blood transfusion.

Methods: We retrospectively reviewed 698 cases of isolated mitral valve surgery with and without combined tricuspid valve operation. Seventy percent of the database was used as the training set and the remainder as the testing set for 13 machine learning algorithms to build a model to predict the need for intraoperative RBC transfusion. According to the characteristic value of model mining, we analyzed the risk-related factors to determine the main effects of variables influencing the outcome.

Results: A total of 166 patients of the cases considered had undergone intraoperative RBC transfusion (24.52%). Of the 13 machine learning algorithms, CatBoost delivered the best performance, with an AUC of 0.888 (95% CI: 0.845–0.909) in testing set. Further analysis using the CatBoost model revealed that hematocrit (<37.81%), age (>64 y), body weight (<59.92 kg), body mass index (BMI) (<22.56 kg/m^2), hemoglobin (<122.6 g/L), type of surgery (median thoracotomy surgery), height (<160.61 cm), platelet (>194.12×10^9/L), RBC (<4.08×10^{12}/L), and gender (female) were the main risk-related factors for RBC transfusion. A total of 204 patients were tested, 177 of whom were predicted accurately (86.8%).

Conclusions: Machine learning models can be used to accurately predict the outcomes of RBC transfusion, and should be used to guide surgeons in clinical practice.

Keywords: Mitral valve; artificial intelligence (AI); blood transfusion; prediction model surgery

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Introduction

Blood transfusion is widely used in surgery. Cardiac surgery uses the largest amount of blood products among surgeries, with a rate of blood transfusion ranging from 40% to 90% (1-3). However, this treatment is a double-edged sword. Transfusion has been associated with high rates of morbidity and mortality in critically ill patients (4). Some recent studies have shown worse outcomes incurred by blood transfusion, including increased renal failure and infection, as well as respiratory, circulatory, and neurological complications after cardiac surgery (5,6). A review of studies on cardiac surgery have shown that red blood cell (RBC) transfusion is associated with an increased risk of postoperative infections and mortality (7-9). It is widely acknowledged blood products are often wasted, where this may reflect a lack of application of evidence-based measures to blood transfusion (10-12). In some instances, the patient's need for RBC transfusion is based on personal experience, and this leads to a waste of blood and burdens the medical staff (13). Transfusion is now recognized as among the most overused treatments in modern medicine (14). Owing to the large amount of blood used and the many factors affecting blood transfusion in cardiac surgery, few studies have used models of blood transfusion in cardiac surgery to examine the issue. Related research used traditional statistical models to predict the relevant factors that affect large volume blood transfusion (LVBT) results in thoraco-abdominal aortic aneurysm (TAAA) surgery. However, only few independent predictors are available for clinical practice (15).

Artificial intelligence (AI) is increasingly being used to aid diagnosis, treatment, automatic classification, and rehabilitation in medicine. The machine learning algorithm is an AI technique designed to simulate human intelligence by discovering patterns of reasoning about the available data (16). Given basic data, machine learning algorithms can be used to predict the relevant information, such as whether blood transfusion is needed. Because patients who have had mitral valve disease have good homogeneity, mitral valve disease has a set of standard procedures for diagnosis and treatment, the comparison of patient data is comparable and are easier to operate on, the amount of bleeding does not change significantly with surgeon during the operation. We use machine learning models to explore the risk-related factors that influence blood transfusion during mitral valve surgery, and accurately provide the boundaries of these factors to guide the surgeon's assessment of patients' need for intraoperative blood transfusion. We present the following article in accordance with the STROBE reporting checklist (available at http://dx.doi.org/10.21037/atm-20-7375).

Methods

The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). This study was approved by the Ethical Committee of Zhongshan Hospital affiliated to Fudan University (No. B2020-218) and individual consent for this retrospective analysis was waived.

Database

The data was drawn from details of 698 patients undergoing isolated mitral or simultaneous tricuspid valve surgery at the Department of Cardiology of Zhongshan Hospital from January to December of 2019, where the surgeries included conventional and minimally invasive approaches. The data included demographic characteristics and the relevant variables before, during, and after surgery. The data extraction techniques included system extraction and manual collection. As usual, the missing values of the measurement data were inserted using the average value while those of counting data were inserted according to the most frequently occurring value.

Patients

Patients who had the maze operation, aortic valve surgery, and atrial septal repair were excluded, as were patients with a history of heart surgeries (excluding interventional therapy). Postoperative complications related to sepsis were defined as those with pathogens that occur in two blood cultures. Preoperative patients were categorized as suffering from mild (HB >90 g/L, but lower than normal), moderate (HB =60–89 g/L), severe (HB =30–59 g/L), and extremely severe anemia (HB <30 g/L) (17). Acute kidney injury (AKI) was defined as an increase in absolute serum creatinine ≥0.3 mg/dL (≥26.5 mol/L) within 48 hours of surgery (18). The severity of all intraoperative valve stenosis or insufficiency was determined according to the results as interpreted by an echocardiographic physician.

Dependent and independent variables

The primary endpoint of this study was "intraoperative red blood cell (RBC) infusion". Intraoperative RBC infusion refers to the amount of allogeneic RBCs initiated to be injected during the operation, excluding autologous and postoperative blood transfusion (15).

Given the aim of establishing a predictive model, the independent variables were chosen by considering the baseline characteristics of the patients in the context of preoperative and intraoperative variables (*Table 1*).

AI model algorithm

The CatBoost algorithm was used to build the AI model. Yandex company proposed and tested the approach using oblivious decision trees as base predictors in 2017 (19) as well as a special method to deal with the characteristics of classification. CatBoost alleviates the problem of overfitting, and improves the generalization ability and robustness of the model, which is particularly suitable for small sample sizes and unbalanced data.

Prediction migration is often a problem in modeling. In each iteration of the gradient boosting decision tree (GBDT), the loss function uses the same dataset to obtain the gradient of the model to train the base learner. This leads to a deviation in the estimated gradient, which in turn leads to the problem of overfitting. CatBoost replaces the method of gradient estimation of the traditional algorithm with order boosting, which reduces bias and improves the generalization ability of the model.

The SHapley Additive exPlanations (SHAP) evaluator proposed by Lundberg and Lee (20) can be used to explain the predictions produced by a model. Following model training, a partial dependency graph (PDP or PD graph) is used to calculate the SHAP value of each feature to allow clinicians to make more accurate predictions. In this way, the impact of each feature on the model can be represented using Shapley values (21). Using these calculations, a matrix of SHAP values can be obtained to provide a visualization of the contribution of each feature to the model predictions. This helps explain the role of each feature in the model in an intuitively understandable way.

Statistical analysis

SPSS 25.0 as well as Python 3.6, with the Python packages Scikit-learn, SHAP (feature analysis), and matplotlib (visualization), were used in. We described the continuous variables of the normal distribution using the mean and standard deviation (SD), the continuous variables of the non-normal distribution using the median and quartile values, and the categorical variables using proportion.

Table 1 Information on variables

Variable name	Subtype	Number
BMI (kg/m^2)		23.75±3.50
Age (year)*	–	58.00 (48.00, 66.00)
Body weight (kg)	–	63.50 (56.00, 72.00)
Height (cm)*	–	165.00 (158.00, 170.00)
INR*	–	1.05 (1.00, 1.12)
Creatinine (μmol/L)*	–	77.00 (65.00, 90.00)
EF (%)*	–	65.00 (61.00, 68.00)
Hematocrit (%)	–	39.36±5.08
Hb (g/L)	–	131.16±18.23
Aspartate transaminase (U/L)*	–	18.00 (15.00, 24.00)
Alanine transaminase (U/L)*	–	17.00 (12.00, 25.00)
RBC (10^{12}/L)*	–	4.33 (3.96, 4.77)
Platelet (10^9/L)*	–	183.00 (151.00, 225.00)
Prothrombin time (s)*	–	11.60 (11.00, 12.30)
Gender	Male	351 (51.85)
	Female	326 (48.15)
Hypertension	No	441 (65.14)
	Yes	236 (34.86)
Diabetes	No	625 (92.32)
	Yes	52 (7.68)
Oral anticoagulants	No	597 (88.18)
	Yes	80 (11.82)
NYHA	1	8 (1.18)
	2	250 (36.93)
	3	51 (7.53)
	4	368 (54.36)
Pulmonary arterial hypertension	No	289 (42.69)
	Yes	388 (57.31)
Atrial fibrillation	No	546 (80.65)
	Yes	131 (19.35)
Infective endocarditis	No	636 (93.94)
	Yes	41 (6.06)
Preoperative anemia	No	589 (87.00)

Table 1 (*continued*)

Table 1 (*continued*)

Variable name	Subtype	Number
ASA	1	78 (11.52)
	2	10 (1.48)
	1	1 (0.15)
	2	26 (3.84)
	3	601 (88.77)
	4	49 (7.24)
Surgeon_id	Doc_1	78 (11.52)
	Doc_2	38 (5.61)
	Doc_3	34 (5.02)
	Doc_4	56 (8.27)
	Doc_5	44 (6.50)
	Doc_6	44 (6.50)
	Doc_7	26 (3.84)
	Doc_8	64 (9.45)
	Doc_9	20 (2.95)
	Doc_10	98 (14.48)
	Doc_11	32 (4.73)
	Doc_12	21 (3.10)
	Doc_13	38 (5.61)
	Doc_14	20 (2.95)
	Doc_15	31 (4.58)
	Doc_16	33 (4.87)
Mitral valve replacement	No	489 (72.23)
	Yes	188 (27.77)
Mitral valve repair	No	249 (36.78)
	Yes	428 (63.22)
Tricuspid valve repair	No	477 (70.46)
	Yes	200 (29.54)
Autologous blood transfusion	No	137 (20.24)
	Yes	540 (79.76)
Tricuspid regurgitation	No	461 (68.09)
	1	99 (14.62)
	2	86 (12.70)
	3	31 (4.58)

Table 1 (*continued*)

Table 1 (*continued*)

Variable name	Subtype	Number
Platelet	<50	0 (0.00)
	50–100	23 (3.40)
	100–150	138 (20.38)
	150–450	514 (75.92)
	>450	2 (0.30)
Age groups	<65	471 (69.57)
	65–74	162 (23.93)
	>75	44 (6.50)
Height groups	<150	18 (2.66)
	150–160	175 (25.85)
	160–170	269 (39.73)
	170–180	177 (26.14)
	>180	38 (5.61)
INR groups	<2	637 (94.09)
	≥2	40 (5.91)
Preoperative cerebral infarction	No	653 (96.45)
	Yes	24 (3.55)
Mitral stenosis	No	517 (76.37)
	1	28 (4.14)
	2	70 (10.34)
	3	62 (9.16)
Mitral regurgitation	No	51 (7.53)
	1	47 (6.94)
	2	264 (39.00)
	3	315 (46.53)
Type of operation	Minimally invasive	216 (31.91)
	Routine	461 (68.09)
Acute coronary syndrome	N	651 (96.16)
	Y	26 (3.84)

*, non-normally distributed variable. Data are presented as mean ± SD, median (Q1, Q3), or n (%). BMI, body mass index; INR, international normalized ratio; ASA, American Society of Anesthesiologists; NYHA, New York Heart Association cardiac function grading; Hb, hemoglobin; EF, ejection fraction.

The Student's *t*-test and was used to identify statistically significant differences between the means of groups. The chi-square test was used to identify any significant association between variables. Mann-Whitney U test was used to compare non-normally distributed variables and variables of ranked data between two groups. First, the variables needed to be screened through univariate analysis to choose the ones with positive results. Second, the screened variables were used for multivariate analysis. We used logistic regression to build a model to mine the relationship between the variables and the outcomes. Third, the machine learning algorithm was used to construct the prediction model for intraoperative blood transfusion. The dataset is randomly divided into training set (70%) and testing set (30%), the training set is implemented to build up a model using 10-fold cross-validation, while the testing set is to validate the model built using the area under the ROC curve (AUC). According to its results, the characteristic values and risk factors were mined to analyze the effects of the latter on the outcome-related variables.

Results

RBC consumption

Of the 677 patients considered, 166 (24.52%) had received intraoperative RBC transfusion, where the amount of RBC transfusion had varied from 2 to 10 Units. The average RBC consumption was 0.71±1.43 Units.

Building traditional models of RBC transfusion

Univariate analysis was performed on all independent variables, and P<0.1 was used for screening. Independent variables with P<0.1 were shown in *Table 2*.

Variables screened by a single factor were entered into the logistic model and screened backward. Variables were eliminated when P>0.1. Those with lower HCT, lower body mass index (BMI), longer PT, females, diabetics, those undergoing routine surgery, patients with atrial fibrillation, severe mitral stenosis, preoperative anemia, and older patients had increased likelihood of the need for of RBC transfusion. In addition, different surgeons are associated with the need for RBC transfusion (*Table 3*).

AI model

The 70% database was used as the training set and 30% as the testing set. Thirteen machine learning algorithms were used for calculation. The training set used 10-fold cross-validation, and the results are shown in the table below. The CatBoost model delivered the best performance with an AUC of 0.888 (95% CI: 0.845–0.909) (*Table 4*).

Further analysis was performed using the CatBoost model, and the importance of the features was analyzed using their SHAP values (*Figure 1*). The main effects of each factor and the outcome variables are shown in *Figure 2*. Different surgeons also influenced this probability (*Figure 3*).

Further analysis using the CatBoost model revealed that hematocrit (<37.81%), age (>64 y), body weight (<59.92 kg), BMI (<22.56 kg/m^2), hemoglobin (<122.6 g/L), type of surgery (median thoracotomy surgery), height (<160.61 cm), platelet (>194.12×10^9/L), RBC (<4.08×10^{12}/L), and gender (female) were the main factors influencing the likelihood of blood transfusion (*Figure 4*).

Figure 2 shows that platelet was positively correlated with RBC transfusion. But its size was related to the coagulation function of the patient. The higher the platelet was, the better the coagulation function was, and the smaller the amount of intraoperative bleeding that occurred. This reduced the probability of transfusion. This variable is further analyzed in *Figure 5*, which shows that the relationship between platelet and RBC transfusion was stratified. When platelet was less than 194.5×10^9/L, platelet was positively correlated with RBC transfusion. When platelet was greater than 203.5×10^9/L, its correlation was negative.

Results of prediction and analysis of RBC transfusion models

A total of 204 patients were tested, with an AUC of 0.922 (95% CI: 0.883–0.956), 177 of whom were predicted accurately (86.8%) and 10 were too large (the patient did not receive a blood transfusion) and 17 were too small (the patient did receive a blood transfusion) (*Table 5*).

The group that was predicted more accurately had more females (80% *vs.* 41.8%), higher age (mean ± SD, 59.2±11.8 *vs.* 53.6±13.9 years), lower weight (mean ± SD, 56.7±8.4 *vs.* 66±13.1 kg), lower height (mean ± SD, 156.9±6.5 *vs.* 165.4±9.1 cm), lower RBC (mean ± SD, 3.7±0.4×10^{12}/L *vs.* 4.4±0.7×10^{12}/L), lower hematocrit (mean ± SD, 34.3%±3.4% *vs.* 40.3%±4.8%), lower preoperative hemoglobin (mean ± SD, 111.5±12.9 *vs.* 134.0±17.5 g/L), more tricuspid valve repair (60% *vs.* 23.2%), and a higher percentage of patients with preoperative anemia (70% *vs.*

Table 2 Comparison of variables by blood transfusion

Variable name	Subtype	Intraoperative blood transfusion		P
		No	Yes	
BMI (kg/m^2)	–	24.30±3.35	22.06±3.42	<0.001
Hematocrit (%)	–	40.57±4.51	35.63±4.93	<0.001
Hemoglobin (g/L)	–	135.55±15.59	117.66±19.19	<0.001
Age (year)	–	56.00 (47.00, 64.00)	65.00 (52.00, 71.00)	<0.001*
Body weight (kg)	–	66.00 (60.00, 75.00)	55.00 (50.00, 62.13)	<0.001*
Height (cm)	–	167.00 (160.00, 172.00)	160.00 (154.75, 165.00)	<0.001*
INR	–	1.04 (0.99, 1.09)	1.08 (1.02, 1.19)	<0.001*
Prothrombin time (s)	–	11.40 (11.00, 12.10)	11.90 (11.30, 13.03)	<0.001*
Red blood cell (10^{12}/L)	–	4.44 (4.09, 4.84)	3.90 (3.64, 4.24)	<0.001*
Gender	Male	303 (86.32)	48 (13.68)	<0.001
	Female	208 (63.80)	118 (36.20)	
Diabetes	No	478 (76.48)	147 (23.52)	0.036
	Yes	33 (63.46)	19 (36.54)	
Oral anticoagulants	No	461 (77.22)	136 (22.78)	0.004
	Yes	50 (62.50)	30 (37.50)	
NYHA	1	8 (100.00)	0 (0.00)	0.011*
	2	196 (78.40)	54 (21.60)	
	3	45 (88.24)	6 (11.76)	
	4	262 (71.20)	106 (28.80)	
Pulmonary arterial hypertension	No	235 (81.31)	54 (18.69)	0.002
	Yes	276 (71.13)	112 (28.87)	
Type of operation	Minimally invasive	189 (87.50)	27 (12.50)	<0.001
	Routine	322 (69.85)	139 (30.15)	
ASA	1	1 (100.00)	0 (0.00)	<0.001*
	2	21 (80.77)	5 (19.23)	
	3	465 (77.37)	136 (22.63)	
	4	24 (48.98)	25 (51.02)	
Atrial fibrillation	No	435 (79.67)	111 (20.33)	<0.001
	Yes	76 (58.02)	55 (41.98)	
Infective endocarditis	No	492 (77.36)	144 (22.64)	<0.001
	Yes	19 (46.34)	22 (53.66)	

Table 2 (*continued*)

Table 2 (*continued*)

Variable name	Subtype	Intraoperative blood transfusion		P
		No	Yes	
Mitral stenosis	Yes	17 (65.38)	9 (34.62)	0.009*
	No	404 (78.14)	113 (21.86)	
	1	15 (53.57)	13 (46.43)	
	2	47 (67.14)	23 (32.86)	
	3	45 (72.58)	17 (27.42)	
Tricuspid regurgitation	No	370 (80.26)	91 (19.74)	<0.001*
	1	68 (68.69)	31 (31.31)	
	2	59 (68.60)	27 (31.40)	
	3	14 (45.16)	17 (54.84)	
Surgeon_id	Doc_1	52 (66.67)	26 (33.33)	<0.001
	Doc_2	34 (89.47)	4 (10.53)	
	Doc_3	23 (67.65)	11 (32.35)	
	Doc_4	46 (82.14)	10 (17.86)	
	Doc_5	33 (75.00)	11 (25.00)	
	Doc_6	32 (72.73)	12 (27.27)	
	Doc_7	24 (92.31)	2 (7.69)	
	Doc_8	61 (95.31)	3 (4.69)	
	Doc_9	18 (90.00)	2 (10.00)	
	Doc_10	54 (55.10)	44 (44.90)	
	Doc_11	20 (62.50)	12 (37.50)	
	Doc_12	14 (66.67)	7 (33.33)	
	Doc_13	27 (71.05)	11 (28.95)	
	Doc_14	18 (90.00)	2 (10.00)	
	Doc_15	27 (87.10)	4 (12.90)	
	Doc_16	28 (84.85)	5 (15.15)	
Mitral valve replacement	No	387 (79.14)	102 (20.86)	<0.001
	Yes	124 (65.96)	64 (34.04)	
Mitral valve repair	No	171 (68.67)	78 (31.33)	0.002
	Yes	340 (79.44)	88 (20.56)	
Tricuspid valve repair	No	374 (78.41)	103 (21.59)	0.006
	Yes	137 (68.50)	63 (31.50)	
Preoperative Anemia	No	480 (81.49)	109 (18.51)	<0.001*
	1	30 (38.46)	48 (61.54)	
	2	1 (10.00)	9 (90.00)	

Table 2 (*continued*)

Table 2 (*continued*)

Variable name	Subtype	Intraoperative blood transfusion		P
		No	Yes	
Platelet	<100	12 (52.17)	11 (47.83)	0.004*
	100–150	97 (70.29)	41 (29.71)	
	150–450	400 (77.82)	114 (22.18)	
	>450	2 (100.00)	0 (0.00)	
Age groups	<65	395 (83.86)	76 (16.14)	<0.001*
	65–74	92 (56.79)	70 (43.21)	
	>75	24 (54.55)	20 (45.45)	
Height groups	<150	13 (72.22)	5 (27.78)	<0.001*
	150–160	102 (58.29)	73 (41.71)	
	160–170	206 (76.58)	63 (23.42)	
	170-180	153 (86.44)	24 (13.56)	
	>180	37 (97.37)	1 (2.63)	
INR groups	<2	487 (76.45)	150 (23.55)	<0.001*
	≥2	24 (60.00)	16 (40.00)	

*, using Mann-Whitney U test. Data are presented as mean ± SD, median (Q1, Q3), or n (%). BMI, body mass index; INR, international normalized ratio; ASA, American Society of Anesthesiologists; NYHA, New York Heart Association cardiac function grading.

Table 3 Final logistic regression model of intraoperative blood transfusion

Risk factors	β	S.E.	χ^2	P	OR	95% CI	
						Lower	Upper
BMI	–0.21	0.04	26.32	<0.01	0.81	0.75	0.88
Prothrombin time	0.03	0.02	2.88	0.09	1.04	0.99	1.08
Hematocrit	–0.17	0.04	14.80	<0.01	0.84	0.77	0.92
Gender							
Male							
Female	1.42	0.33	18.23	<0.01	4.13	2.15	7.92
Diabetes							
No							
Yes	0.90	0.44	4.07	0.04	2.45	1.03	5.86
Type of operation							
Minimally invasive							
Routine	1.35	0.41	10.94	<0.01	3.84	1.73	8.54
Atrial fibrillation							
No							

Table 3 (*continued*)

Table 3 (*continued*)

Risk factors	β	S.E.	χ^2	P	OR	95% CI	
						Lower	Upper
Yes	1.07	0.39	7.47	<0.01	2.91	1.35	6.27
Mitral stenosis			7.16	0.07			
No							
1	1.01	0.55	3.35	0.07	2.76	0.93	8.16
2	–0.13	0.42	0.09	0.76	0.88	0.38	2.02
3	–0.79	0.50	2.46	0.12	0.45	0.17	1.22
Surgeon_id			59.78	<0.01			
Doc_1							
Doc_2	–1.60	0.85	3.55	0.06	0.20	0.04	1.07
Doc_3	0.38	0.60	0.39	0.53	1.46	0.45	4.76
Doc_4	–1.09	0.59	3.47	0.06	0.34	0.11	1.06
Doc_5	–0.46	0.63	0.53	0.47	0.63	0.18	2.18
Doc_6	0.34	0.59	0.33	0.57	1.40	0.44	4.49
Doc_7	–2.58	0.99	6.81	<0.01	0.08	0.01	0.53
Doc_8	–2.38	0.91	6.78	<0.01	0.09	0.02	0.56
Doc_9	–2.42	0.97	6.21	0.01	0.09	0.01	0.60
Doc_10	0.79	0.49	2.52	0.11	2.19	0.83	5.78
Doc_11	0.96	0.61	2.51	0.11	2.61	0.80	8.58
Doc_12	0.95	0.72	1.74	0.19	2.57	0.63	10.50
Doc_13	–1.19	0.64	3.46	0.06	0.30	0.09	1.07
Doc_14	–1.52	1.02	2.22	0.14	0.22	0.03	1.61
Doc_15	–2.71	0.84	10.31	<0.01	0.07	0.01	0.35
Doc_16	–0.35	0.74	0.23	0.63	0.70	0.17	2.98
Tricuspid valve repair							
No							
Yes	–0.71	0.36	3.87	0.05	0.49	0.24	1.00
Preoperative anemia			13.17	<0.01			
No							
1	1.45	0.44	10.77	<0.01	4.27	1.79	10.14
2	3.20	1.33	5.76	0.02	24.43	1.80	331.89
Age			36.62	<0.01			
<65							
65–74	1.70	0.30	32.82	<0.01	5.49	3.07	9.83
>75	1.62	0.48	11.64	<0.01	5.07	2.00	12.89

Table 4 Comparison of the results of machine learning models

	Model	Accuracy	AUC	Recall	Prec.	F1
1	CatBoost classifier	0.835	0.888	0.536	0.731	0.609
2	Light gradient boosting machine	0.844	0.887	0.579	0.732	0.640
3	Extreme gradient boosting	0.844	0.874	0.552	0.745	0.629
4	Gradient boosting classifier	0.823	0.860	0.536	0.706	0.594
5	Extra trees classifier	0.808	0.857	0.433	0.706	0.521
6	Logistic regression	0.823	0.856	0.571	0.689	0.609
7	Linear discriminant analysis	0.820	0.851	0.588	0.662	0.611
8	Random forest classifier	0.816	0.835	0.408	0.741	0.515
9	Ada boost classifier	0.791	0.812	0.536	0.603	0.554
10	Naive bayes	0.702	0.803	0.821	0.449	0.578
11	K neighbors classifier	0.787	0.751	0.328	0.563	0.408
12	Decision tree classifier	0.768	0.681	0.510	0.525	0.506
13	Quadratic discriminant analysis	0.435	0.613	0.885	0.313	0.444

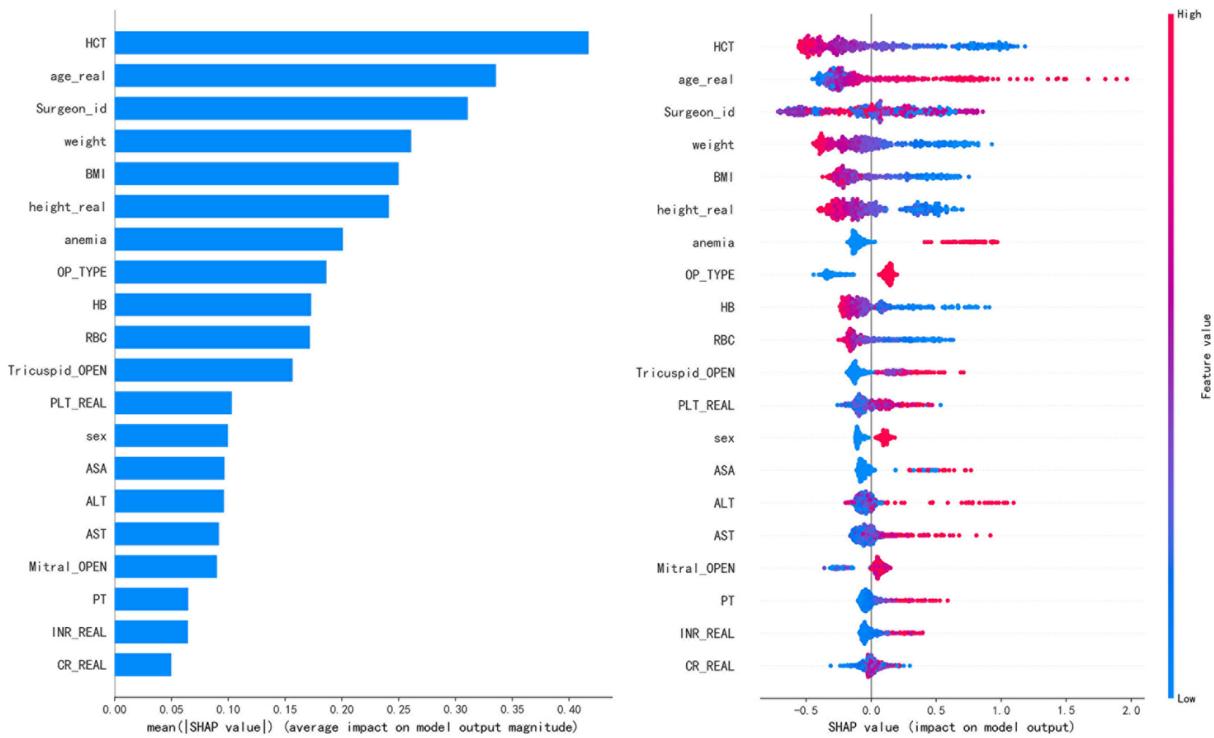

Figure 1 Plots of the importance of the variables and the SHAP variable. The red dots represent large values and the blue dots low values. The former shows the importance of variables for predicting the likelihood of RBC transfusion, sorted by importance from high to low. The latter shows the importance of the value of each variable in predicting the likelihood of RBC transfusion. The red dots represent large values and the blue dots low values. HCT, hematocrit; BMI, body mass index; RBC, red blood cell; OP_TYPE, type of operation; Hb, hemoglobin; ASA, American Society of Anesthesiologists; PLT, platelet; AST, aspartate transaminase; ALT, alanine transaminase; PT, prothrombin time; INR, international normalized ratio; NYHA, New York Heart Association cardiac function grading; SHAP, SHapley Additive exPlanations.

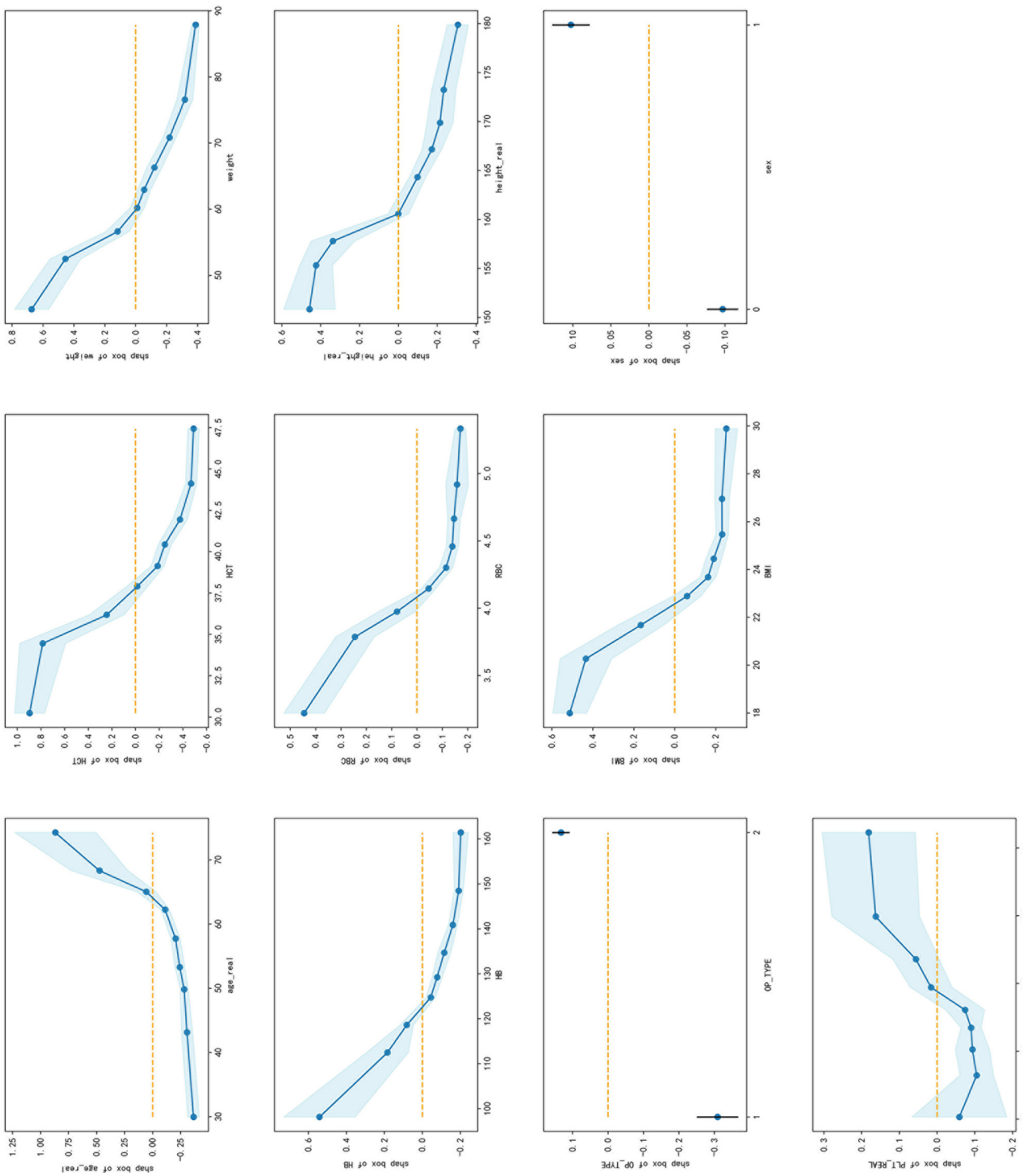

Figure 2 Main effects of each risk factor and outcome variable. The risk factors included age, hematocrit, body weight, hemoglobin, red blood cells, height, surgical approaches, BMI, gender, and PLT. BMI, body mass index; PLT, platelet.

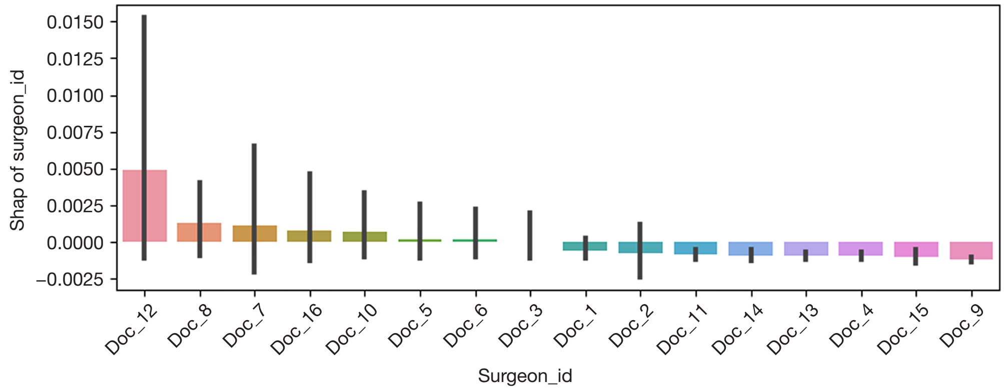

Figure 3 SHAP value for the surgeon. When it is greater than 0, the surgeon was more likely to transfuse the patient. SHAP, SHapley Additive exPlanations.

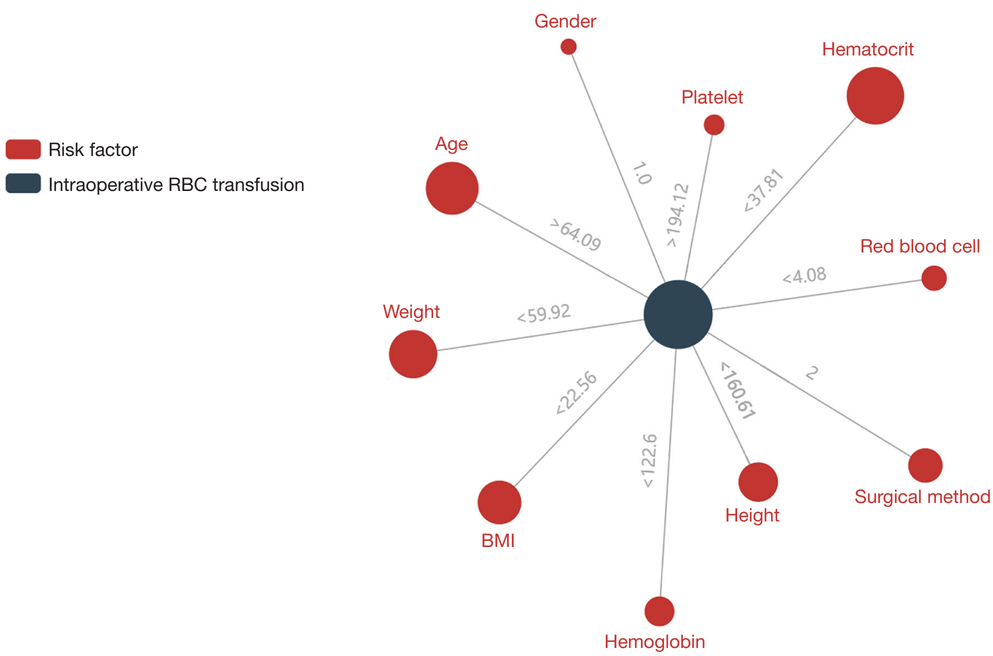

Figure 4 Analysis of factors influencing intraoperative RBC transfusion. BMI, body mass index;

8.5%).

Discussion

Table 3 shows that the factors influencing blood transfusion extracted from the traditional logistic regression model. *Figure 1* shows that the machine learning model identified the influential factors. Thus, the factors excavated by the machine learning model and logistic model were roughly the same. Moreover, the factors identified by our model were consistent with the conclusions of previous studies (13). In addition, the machine learning model accurately gave the specific boundary values of the factors. (*Figure 4*), which will help clinicians in their judgment of blood transfusion in patients undergoing preoperative surgery.

Research on predicting the need for transfusion in cardiac surgery is rare. Many factors affect the blood used in cardiac surgery, and the traditional model cannot identify

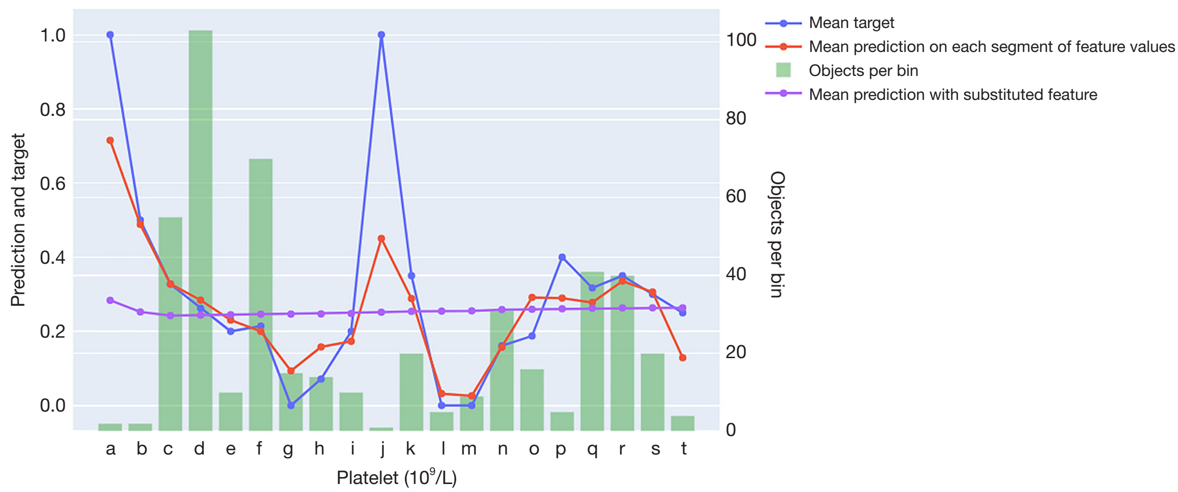

Figure 5 Further analysis of platelet. We compared and analyzed values from the original data and those predicted by the model.

Table 5 Analysis of results of prediction

Variables	Overall (n=204)	Too large (n=10)	Too small (n=17)	Correct (n=177)	P
Sex, n (%)					0.027
Male	112 (54.9)	2 (20.0)	7 (41.2)	103 (58.2)	
Female	92 (45.1)	8 (80.0)	10 (58.8)	74 (41.8)	
Age, mean (SD)	54.9 (13.8)	59.2 (11.8)	65.9 (7.3)	53.6 (13.9)	0.001
weight, mean (SD)	64.9 (13.0)	56.7 (8.4)	58.3 (10.8)	66.0 (13.1)	0.007
Height, mean (SD)	164.6 (9.1)	156.9 (6.5)	160.1 (6.7)	165.4 (9.1)	0.001
Red blood cell, mean (SD)	4.4 (0.7)	3.7 (0.4)	4.2 (0.5)	4.4 (0.7)	0.003
Hematocrit, mean (SD)	39.9 (4.8)	34.3 (3.4)	38.9 (4.0)	40.3 (4.8)	<0.001
Hemoglobin, mean (SD)	132.5 (17.8)	111.5 (12.9)	129.1 (15.0)	134.0 (17.5)	<0.001
Tricuspid valve repair, n (%)					0.032
No	153 (75.0)	4 (40.0)	13 (76.5)	136 (76.8)	
Yes	51 (25.0)	6 (60.0)	4 (23.5)	41 (23.2)	
Preoperative anemia, n (%)					<0.001
No	181 (88.7)	3 (30.0)	16 (94.1)	162 (91.5)	
1	22 (10.8)	7 (70.0)	1 (5.9)	14 (7.9)	
2	1 (0.5)			1 (0.6)	

all factors influencing this or predict whether patient needs intraoperative blood transfusion (22). We use the machine learning to build a model to predict the need for blood transfusion among patients, and yielded an accuracy of up to 86.8%. The model can play an important role in clinical guidance.

Based on clinical observations, some researchers have suggested that hematocrit should be maintained at around 30% and hemoglobin concentration at 10 g/dL (23). However, this threshold has been reconsidered due to risks associated with transfusion and a greater appreciation of the importance of varying physiological responses to anemia (24). Due to the particularity of heart surgery, intraoperative extracorporeal circulation requires the heparinization of the patient's blood, and the operating time is long. This increases the risk of intraoperative bleeding. Our machine learning model thus considered cases of intraoperative heparin and the duration of the operation. The dangerous boundary of hemoglobin content was found at 12 g/dL and hematocrit to be 38%.

When platelet was less than 194.5, platelet was positively correlated with RBC transfusion. When platelet was greater than 203.5, its correlation was negative. We think that the increase in platelet was not due to each patient's thrombocytosis, but perhaps because of acute infection, blood loss, or hemolysis. This suggests that patient might already have lost blood to increase the likelihood of the need for blood transfusion (25).

We used the machine learning model to analyze the surgeons, and found that Doctor 12 (33.3%, 0.76±1.19 U), Doctor 8 (4.7%, 0.22±1.29 U), and Doctor 7 (7.7%, 0.42±1.65 U) were positively correlated with the likelihood of blood transfusion. Subsequent studies can use machine learning models to intervene in the doctors' choice of administering blood transfusion to reduce the unnecessary use of blood (*Figure 3*).

Tables 2,3 and *Figures 1,2,4* shows that women (36.2%, 1.06±1.62 U) were more likely to receive blood transfusion. Owing to physical blood loss, many women develop anemia during surgery, which was the direct cause of their high intraoperative blood transfusion rate (26). The mode of surgery was also an important factor. The traditional surgical method involves direct midline thoracotomy into the heart while the minimally invasive method involves using the intercostal space to enter the area without requiring midline thoracotomy. Compared with the traditional surgery group (30.2%, 0.88±1.56), minimally invasive surgery (12.5%, 0.36±1.01) can significantly reduce the amount of blood needed, which is consistent with previous reports (27). Tricuspid valve repair was also an important factor influencing blood transfusion in the traditional model and the machine learning model. Functional regurgitation is noted during mitral valve surgery, synchronous repair (class I) is recommended (28). The tricuspid valve regurgitation can cause anemia, thrombocytopenia, coagulation disorders, hepatic failure, and other complications (29), leading to a higher likelihood of the need for blood transfusion.

Although our data were relatively complete and accurate, the analysis was retrospective and covered a single center. Short-term postoperative analysis was carried out for cases of incorrect prediction, but the relevant patients were not followed up with to better understand the impact of blood transfusion on their recovery. Our model is undergoing further development, and does not predict the amount of blood needed for transfusion. Moreover, it can predict the need for blood transfusion for only one type of surgery.

Conclusions

We used machine learning model to predict the need for RBC transfusion in cardiac surgery. It can help guide surgeons in clinic al practice.

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Footnote

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Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). This study was approved by the Ethical Committee of Zhongshan Hospital affiliated to Fudan University (No. B2020-218) and individual consent for this retrospective analysis was waived.

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