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RESEARCH

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An explainable and supervised machine learning model for prediction of red blood cell transfusion in patients during hip fracture surgery

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Abstract

Aim The study aimed to develop a predictive model with machine learning (ML) algorithm, to predict and manage the need for red blood cell (RBC) transfusion during hip fracture surgery.

Methods Data of 2785 cases that underwent hip fracture surgery from April 2016 to May 2022 were collected, covering demographics, medical history and comorbidities, type of surgery and preoperative laboratory results. The primary outcome was the intraoperative RBC transfusion. The predicting performance of six algorithms were respectively evaluated with the area under the receiver operating characteristic (AUROC). The SHapley Additive exPlanations (SHAP) package was applied to interpret the Random Forest (RF) model. Data from 122 patients at The Third Affiliated Hospital of Sun Yat-sen University were collected for external validation.

Results 1417 patients (50.88%) were diagnosed with preoperative anemia (POA) and 209 patients (7.5%) received intraoperative RBC transfusion. Longer estimated duration of surgery, POA, older age, hypoproteinemia, and surgery of internal fixation were revealed as the top 5 important variables contributing to intraoperative RBC transfusion. Among the six ML models, the RF model performed the best, which achieved the highest AUC (0.887, CI 0.838 to 0.926) in the internal validation set. Further, it achieved a comparable AUC of 0.834(0.75, 0.911) in the external validation set.

Conclusion Our study firstly demonstrated that the RF model with 10 common variables might predict intraoperative RBC transfusion in hip fracture patients.

Key points

-Question: [How do we predict intraoperative RBC transfusion in hip fracture patients prior to surgery?].

-Findings: [Our study firstly demonstrated that the RF model with 10 common variables might predict intraoperative RBC transfusion in hip fracture patients.]

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-Meaning: [The predictive model is designed to reduce intraoperative ABT in hip fracture surgery by identifying the high-risk patients before surgery, so that proper measures can be taken beforehand.]

Keywords Hip fracture, Red blood cell transfusion, Machine learning, Predictive model, SHapley Additive exPlanations

Introduction

There're 1.6 million people suffered from hip fractures each year worldwide, and the number will continue to increase by 25% in the next decade due to population growth [1, 2]. The mortality rate associated with hip fracture is considerable and surgical intervention is the primary treatment. Various surgical techniques are employed depending on the location and severity of the fracture, such as internal repair with screws and total/partial hip replacement [3].

More than one-third of the elderly patients undergoing total hip replacement have been reported to experience anemia, and numerous studies indicated that anemia is associated with an increased risk of surgical complications in this population [4, 5]. Perioperative anemia has been identified as a significant predictor of heightened complications and mortality following hip fracture surgery in several studies [2, 6, 7]. The majority of patients require concentrated red blood cell (RBC) transfusions during or after surgery, to enhance oxygen supply and tissue perfusion. It's reported that the perioperative blood loss of total hip arthroplasty was ranging from 700 to 2000 mL [8], and 16% to 37% of patients required intraoperative allogeneic blood transfusion (ABT) [9]. Despite the availability of several techniques to mitigate blood loss during surgical procedures, including the use of tranexamic acid (TXA), intraoperative blood salvage, and autologous blood transfusion, ABT remains the predominant approach for managing perioperative anemia, given its perceived benefits and cost-effectiveness [10, 11]. However, patients experienced massive blood loss during the surgery might need emergency transfusion which may not always be available due to shortage of blood supply. ABT may also cause risks of virus infection, immune allergic reaction, transfusion-related hemolysis, and lung injury. Therefore, it will be more effective to implement a proper blood management strategy by identifying patients at risk for intraoperative RBC transfusion before surgery.

Numerous studies have been conducted to identify risk factors for perioperative ABT using traditional regression-based algorithms [12–15]. Given that various factors had been identified to be associated with intraoperative RBC transfusion, including age, preoperative hemoglobin (Hb) level, American Society of Anesthesiologists physical status classification (ASA), frailty, and operative time, type of surgery and fracture, body weight index (BMI), general anesthesia (GA) [16–20], there is a need for more robust methodologies to assess the impact of these factors on ABT. In recent studies, machine learning (ML) demonstrated efficacy in constructing predictive models for diseases or medical outcomes. ML is a branch of artificial intelligence (AI) and computer science that focuses on finding data connections that are linear, nonlinear or even data with a heterogeneous nature which exhibits an advantage over traditional regression-based algorithms. Zhang et al. built a highly interoperable tool across institutions for early detection of acute kidney injury after adult deceased donor liver transplantation using ML-algorithm [21]. The ML algorithms build mathematical models based on the sample data known as "training data", to make predictions or decisions without being programmed to do so. The administration of RBC transfusions during surgery may be impacted by numerous factors that require extensive data processing, making ML a valuable tool. ML has been employed in predicting postoperative mortality of elderly patients with hip fractures, but there is still limited study focusing on the early prediction of ABT for those with hip fractures. Wang et al. and Zhang et al. developed their prediction model for perioperative ABT in hip fracture patients using a nomogram model and exhibited satisfactory performance [22, 23]. We consider it will be of better use to build a reliable and operable tool for preoperative recognition of hip fracture patients at high risk for ABT, which assists decision-making before surgery.

This study aimed to identify preoperative factors linked to intraoperative RBC transfusion in patients undergoing primary unilateral hip fracture surgery and subsequently develop an ML model for predicting RBC transfusion during surgery.

Materials and methods

Study subjects

The study was approved by the ethics committee of Guangdong Provincial Hospital of Chinese Medicine (No. ZE2023-201–01). and the requirement for written informed consent was waived by the committee. In the study, patients undergoing hip fracture surgery in Guangdong Provincial Hospital of Chinese Medicine from April 2016 to May 2022 were enrolled, and those admitted with multiple injuries or underwentrevision surgery, bilateral hip arthroplasty or internal fixation of femur were excluded.

Patients were divided into the Transfusion Group or Non-transfusion Group depending on whether they received RBC transfusion during hip fracture surgery or not.

Primary outcome

The primary outcome of the study was defined as a ML model for predicting intraoperative RBC transfusion of patients undergoing hip fracture surgery.

Predictors and selection

Combined with previous literature and the aim of our study, a total of 15 features were collected from the electronic medical record of our hospital: patient demographic characteristics (e.g. gender, age, BMI), comorbidities [e.g. hypertension, diabetes mellitus, stroke, cardiac diseases, lower limb deep venous thrombosis (DVT)], surgical data (e.g. type of anesthesia, ASA, types of surgery, estimated duration of surgery), laboratory indicators [Hb, serum albumin (ALB), serum total protein (TP)]. All of the data were collected from the electronic medical record and anesthesia records of our hospital. For variables with multiple measurements, the values closest to the surgery were adopted.

Preoperative anemia (POA) was diagnosed with Hb < 130 g/L for men and Hb < 120 g/L for non-pregnant women [24]. DVT was diagnosed by the indication of venous thrombosis in the lower limbs with preoperative ultrasonography. Hypoproteinemia was diagnosed with serum concentration of ALB < 35 g/L or TP < 60 g/L. Hip fracture surgery is typically performed under either GA or spinal anesthesia (SA). The wait time to surgery is the interval between admission and the commencement of surgery. The estimated duration of surgery was assessed from the electronic anesthesia record system.

To minimize potential over-fitting brought by the high dimensionality of the features, only statistically significant features ($p < 0.05$) in univariate tests were chosen and subjected to a least absolute shrinkage and selection operator (LASSO) regression approach. Eventually, features with non-zero coefficients after LASSO regression were used for model development.

Transfusion protocol

The intraoperative RBC transfusion protocol adhered to by our department aligns with the "Guideline for perioperative patient blood management (WS/T 796—2022)" which is a national standard issued by the National Health Commission of the People's Republic of China [25]. As per these guidelines, patients exhibiting a Hb level exceeding 100 g/L typically do not necessitate blood transfusion, whereas individuals with an Hb level below 70 g/L require transfusion. Clinicians should exercise their discretion in determining the need for red blood cell transfusion in patients with hemoglobin levels ranging from 70 g/L to 100 g/L, taking into account various factors such as the patient's age, bleeding risk associated with the upcoming procedure, cardiopulmonary function, and metabolic rate.

Statistical analysis

Training dataset and validation dataset

The entire cohort was randomly separated into an 80% training set used for model development and a 20% validation set. Bootstrap method was used to get 95% confidence interval (CI) of the best-tuned models' evaluation metrics. The missing values were imputed using a simple imputation method. We imputed categorical variables with the mode and continuous variables with the median. Continuous variables were standardized using the Z-score. Categorical variables were encoded into binary variables, 1 represents having an incident, and 0 represents not having an incident. Gender, type of surgery, and anesthesia were also encoded, 1 represents male/arthroplasty/GA, and 0 represents female/internal fixation/SA.

Model development

We developed our prediction model of RBC transfusion during hip fracture surgery based on 6 algorithms, including extreme gradient boosting (XGB), gradient boosting decision tree (GBDT), support vector machine (SVM), multi-layer perceptron (MLP), Logistic regression (LR), random forest (RF). All of the models were used to predict intraoperative RBC transfusion with patient preoperative characteristics. Bootstrap method with 1000 replications was used to get the 95% CI of the best-tuned models' evaluation metrics. Grid search method with five-fold cross-validation was used to choose the best hyperparameters for each model. Grid search involves setting several candidate parameters for each hyperparameter used in a machine-learning model. Using an exhaustive method, it iteratively trains and validates the model, ultimately selecting the set of hyperparameter combinations that yield the highest area under the curve (AUC) for the model. The predictive ability of each model was determined by the area under the curve (AUC) of the receiver operating characteristic (ROC). Eventually, the validation set was subjected to SHAP package analysis in Python to interpret RF models using Shapely values. SHAP method was implemented using Python shap package (https://shap.readthedocs.io/en/latest/).

Data from patients who underwent hip fracture surgery from December 2022 to February 2023 were collected prospectively in the Third Affiliated Hospital of Sun Yat-sen University to further validate the proposed model. The framework for developing each ML-based predictive model is shown in Fig. 1.

Other statistical methods

The entire dataset underwent a univariate statistical test. A normality test was conducted on the continuous variables, and it was determined that they followed a normal distribution. Consequently, independent t-tests were utilized for the continuous variables, while Chi-square tests were employed for the categorical variables to evaluate disparities between the transfusion and non-transfusion groups. All statistical analyses were executed in Python (Anaconda Distribution version 3.8.2).

Results

Patient population and demographics

In this study, 3075 patients who underwent hip fracture surgery were assessed. We excluded 224 patients with secondary surgery, revision surgery, bilateral hip arthroplasty or internal fixation of the femur. Additionally, 66 patients were also excluded for lacking sufficient data. 2785 patients were finally included in this study and the demographics and preoperative information of the cohort were displayed in Table 1. The average age of patients was 67.72 years, women accounted for 61.54%, and the average BMI was 23.19. In this study, 1417 patients were diagnosed as POA, accounting for 50.88% of the cohort, and 209 (7.5%) of the patients received intraoperative RBC transfusion.

Feature selection using LASSO regression

As shown in Fig. 2, 10 variables were indicated to be associated with intraoperative RBC transfusion, including age, gender, POA, ASA, diabetes, history of stroke, hypoproteinemia, wait time to surgery, estimated duration of surgery, and types of surgery ($p < 0.001$). Further, feature importance plot was created to rank the level of importance. As a result, types of surgery, estimated duration of surgery, and preoperative hypoproteinemia were ranked first, second, and third, respectively.

Performance assessment of the ML models

As we can see from Table 2 and Fig. 3, the predictive efficacy of all six models in predicting RBC transfusion was deemed satisfactory. Among the models, the RF model achieved the best AUC (0.887, 95% CI 0.838–0.926), the highest accuracy (0.79, 95% CI 0.756–0.822), and sensitivity (0.906, 95% CI 0.811–0.979), relatively balanced specificity (0.781, 95% CI 0.745–0.816). The RF model surpassed the other five models in predictive performance, therefore we built our ML model based on the RF algorithm.

Appendix Table S1 showed the initial hyperparameters sets and the best hyperparameter combination for each model.

External validation

Data of 122 patients were collected for external validation, of which 60 (49%) received intraoperative transfusion. The external validation set has similar duration of surgery and preoperative wait time (Table 3). The incidence of hypoproteinemia and POA was higher in the external validation group compared to that of the training set (54.92% vs 18.94%, 82.25% vs 51.03%, $p < 0.001$). The proportion of female is slightly higher in the external validation set (76.23% vs 61.80%, $p < 0.001$). Besides, most surgeries were performed under general anesthesia both in training set and external validation set. In this external validation set, the RF model achieved a comparable AUC (0.834, CI 0.75 to 0.91) to that of the internal validation set (Fig. 4).

SHAP analysis of the model

The results depicted in Fig. 5 showed the feature importance ranking based on SHAP values in RF model. Longer estimated duration of surgery, POA, older age, hypoproteinemia and surgery of internal fixation were revealed by SHAP method the top 5 important variables contributing to intraoperative RBC transfusion.

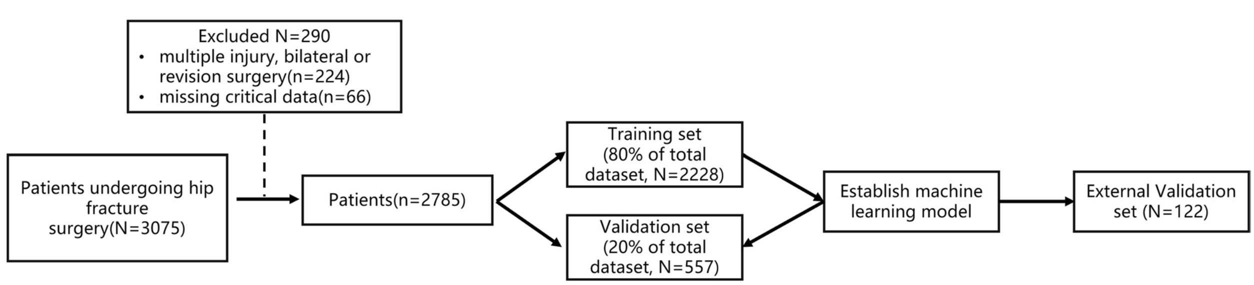

Fig. 1 The framework for developing an ML-based predictive model

Table 1 Patient demographics and preoperative features

Variables	All $N=2785$	Non-transfusion $N=2576$	Transfusion $N=209$	P^b value
Age, mean(SD)	67.72(15.16)	67.09(14.97)	75.55(15.31)	**< 0.001**
Gender, n(%)				**< 0.001**
Female	1714(61.54%)	1568(60.87%)	146(69.86%)	
Male	1071(38.46%)	1008(39.13%)	63(30.14%)	
BMI, mean(SD)	23.19(6.54)	23.22(6.75)	22.78(2.94)	0.232
Anesthesia, n(%)				**< 0.001**
SA	944(33.90%)	841(32.65%)	103(49.28%)	
GA	1841(66.10%)	1735(67.35%)	106(50.72%)	
POA, n(%)	1417(50.88%)	1240(48.14%)	177(84.69%)	**< 0.001**
ASA, n(%)				**< 0.001**
I	34(1.22%)	32(1.24%)	2(0.96%)	
II	1619(58.13%)	1550(60.17%)	69(33.01%)	
III	1083(38.89%)	955(37.07%)	128(61.24%)	
IV	49(1.76%)	39(1.51%)	10(4.78%)	
Hypertension, n(%)	1225(43.99%)	1108(43.01%)	117(55.98%)	**< 0.001**
Diabetes, n(%)	526(18.89%)	487(18.91%)	39(18.66%)	0.931
Cardiac diseases, n(%)	1705(61.22%)	1574(61.10%)	131(62.68%)	0.653
Stroke, n(%)	388(13.93%)	339(13.16%)	49(23.44%)	**< 0.001**
Hypoproteinemia, n(%)	520(18.67%)	429(16.65%)	91(43.54%)	**< 0.001**
DVT, n(%)	117(4.20%)	107(4.15%)	10(4.78%)	0.662
Types of surgery, n(%)				**< 0.001**
Hip replacement	1943(69.77%)	1869(72.55%)	74(35.41%)	
Internal fixation	842(30.23%)	707(27.45%)	135(64.59%)	
Wait time to surgery, n(%)	89.58(62.62)	88.17(61.73)	106.89(70.60)	**< 0.001**
Estimated duration of surgery, mean(SD)	1.54(0.63)	1.49(0.57)	2.11(0.91)	**< 0.001**

SD standard deviation, *ASA* American Society of Anesthesiologists physical status classification, *POA* preoperative anemia, *SA* spinal anesthesia, *GA* general anesthesia, *BMI* Body mass index, *DVT* Deep venous thrombosis

p^b value calculated using independent t-test, and Pearson Chi-square test. The bold emphasis means that $p < 0.05$

Application of the model

To optimize the application of the model in clinical settings, a web page was established to enable clinicians to assess the probability of RBC transfusions during hip fracture surgery. (https://analysis.aidcloud.cn/cn/hip/).

For instance, the preoperative information of a patient was input into the model: age 84 years, female gender, no history of stroke, ASA class II, diagnosed with POA (Hb 110 g/L) and hypoproteinemia (ALB 34 g/L, TP 75 g/L), waited 186 h before surgery, with estimated 2 h of surgery, undergoing surgery of internal fixation under SA. The analysis conducted by the model revealed a 94.00% risk of RBC transfusion for this patient, indicating a high probability of requiring RBC transfusion. Consequently, the model recommended RBC transfusion for this patient (Fig. 6A).

Similarly, the preoperative information of another patient was input into the model: age 57 years, female sex, ASA class II, no history of stroke, no POA ((Hb 134 g/L)) nor hypoproteinemia (ALB 40 g/L, TP 79 g/L), waited 49 h before surgery, with estimated 1.5 h of surgery, undergoing surgery of hip under GA. The predicted probability of transfusion in this patient was 39.00%, indicating that the patient was at low risk of requiring RBC transfusion. (Fig. 6B).

Discussion

Early detection of intraoperative RBC transfusion for hip patients prior to surgery is critical for the preparation of blood products and the proper initiation of blood management strategy. The prediction of intraoperative RBC transfusion based on preoperative patient characteristics is challenging, and few studies have been conducted on this issue. In this study, a large volume of data was processed with ML method, the major findings are as follows, (1) the incidence of POA for hip fracture patients was as high as 50.88% and 7.5% of patients received intraoperative RBC transfusion; (2) 10 preoperative variables were indicated significantly correlated to intraoperative RBC transfusion in hip fracture patients, including age,

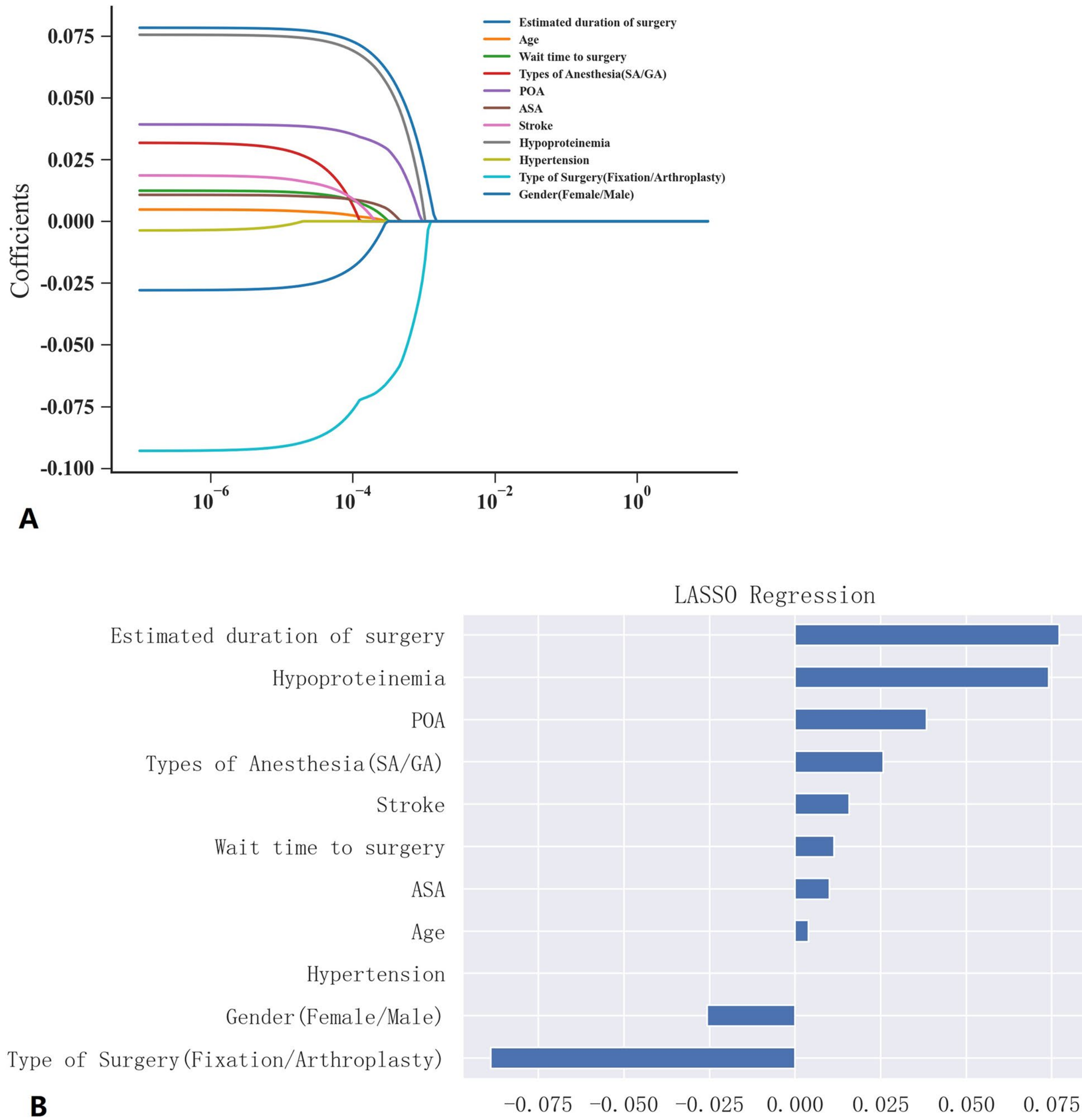

Fig. 2 Primary predictive variables screening based on LASSO regression. **A** The horizontal axis lambda represents the penalty term in LASSO, and the vertical axis represents the coefficients of the variables in the LASSO regression. The closer the lambda value is to 1, the smaller the coefficients of the variables in the LASSO regression, and vice versa. The optimal lambda value of 0.00003 was obtained by cross validation method, at which point the coefficients of 10 variables were not equal to 0, thus resulting in 10 variables being selected by the LASSO. **B** The horizontal axis represents the coefficients of the variables in the LASSO regression, where the coefficient of Hypertension is 0, and the coefficients of other variables are not 0, thus resulting in 10 variables being selected by the LASSO variable selection

gender, POA, ASA, diabetes, history of stroke, hypoproteinemia, wait time to surgery, estimated duration of surgery, types of surgery; (3) the RF model exhibited the best overall performance in predicting intraoperative among the developed ML models, with the value of AUC of 0.887, the sensitivity of 90.6%, and specificity of 78.1%;(4) a web page was established to facilitate the clinical use of this predictive model.

As the aging population continues to grow, the occurrence of fragility hip fractures is increasing annually,

Table 2 Performance of different machine learning algorithms in predicting intraoperative RBC transfusion in the validation set

Model	AUC	Accuracy	Sensitivity	Specificity	F1
LR	0.872(0.817, 0.916)	0.79(0.752, 0.82)	0.789(0.653, 0.903)	0.789(0.75, 0.821)	0.36(0.261, 0.442)
SVM	0.882(0.832, 0.924)	0.781(0.747, 0.815)	0.931(0.848, 1.0)	0.769(0.732, 0.805)	0.389(0.301, 0.473)
RF	0.887(0.838, 0.926)	0.79(0.756, 0.822)	0.906(0.811, 0.979)	0.781(0.745, 0.816)	0.396(0.3, 0.48)
LGB	0.878(0.821, 0.924)	0.761(0.725, 0.799)	0.864(0.744, 0.956)	0.754(0.716, 0.791)	0.352(0.272, 0.441)
XGB	0.877(0.817, 0.919)	0.77(0.734, 0.804)	0.833(0.714, 0.939)	0.766(0.728, 0.802)	0.352(0.265, 0.431)
MLP	0.883(0.835, 0.924)	0.79(0.754, 0.822)	0.909(0.811, 0.978)	0.781(0.744, 0.814)	0.392(0.308, 0.474)

Bootstrap method was used to get 95% confidence interval (CI) of the best tuned models' evaluation metrics

Abbreviations: *AUC* Area Under Curve, *F1* F1-score, *XGB* Extreme Gradient Boosting, *GBDT* Gradient Boosting Decision Tree, *SVM* Support Vector Machine, *MLP* Multi-Layer Perceptron, *LR* Logistic Regression, *RF* Radom Forest

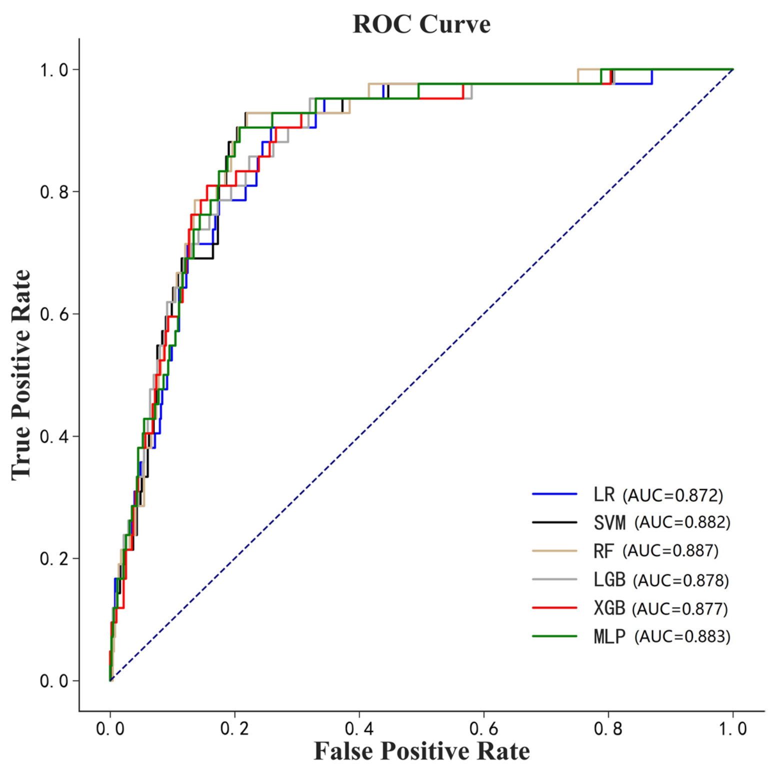

Fig. 3 Receiver operating characteristic curves for the machine learning model and logistic regression, Extreme Gradient Boosting(XGBOOST), Gradient Boosting Decision Tree(GBDT), Support Vector Machine(SVM), Multi-Layer Perceptron(MLP), Logistic Regression(LR), Radom Forest(RF)

resulting in a greater number of elderly patients with comorbidities and poor health requiring total hip replacement or internal fixation [1]. POA is prevalent among hip fracture patients, with Jiang et al [26].. reporting a 55.4% incidence of anemia upon admission. The authors also suggested that even mild POA is linked to significant postoperative complications in hip fracture patients. Our study showed that 50.88% of the patients were admitted with anemia, and the incidence of RBC transfusion during hip fracture surgery is 7.5%, which was consistent with a recent publication [27]. ABT is the primary treatment for anemia and has been shown to improve patients' hemodynamic status and reduce postoperative complications due to blood loss [28]. However, it might also linked to transfusion-related complications and potentially increase long-term mortality [29]. Numerous studies have indicated that ABT may lead to postoperative infection [30], delirium [31], prolonged hospital stay [32, 33], increased mortality [34, 35], delayed functional recovery [36] and DVT [37]. Therefore, it is crucial to anticipate the need for intraoperative

Table 3 Comparison of training set and the external validation set

Variable	Training set (N = 2228)	External validation set (N = 122)	P_values
Age	67.54(15.34)	78.28(9.70)	< 0.001
Estimated duration of surgery(h)	1.54(0.63)	1.86(1.18)	0.166
Wait time to surgery(h)	89.77(62.46)	100.21(72.75)	0.199
POA(n)	1137(51.03%)	104(85.25%)	< 0.001
ASA			< 0.001
I	28(1.26%)	55(45.08%)	
II	1301(58.39%)	67(54.92%)	
III	859(38.55%)	0(0%)	
IV	40(1.80%)	0(0%)	
Hypoproteinemia	422(18.94%)	67(54.92%)	< 0.001
Types of surgery			< 0.001
Internal fixation	678(30.43%)	86(70.49%)	
Hip replacement	1550(69.57%)	36(29.51%)	
Gender (female, n)	1377(61.80%)	93(76.23%)	< 0.001
Stroke	298(13.38%)	5(4.10%)	0.003
Types of Anesthesia (GA, n)	1460(65.53%)	85(69.67%)	0.348

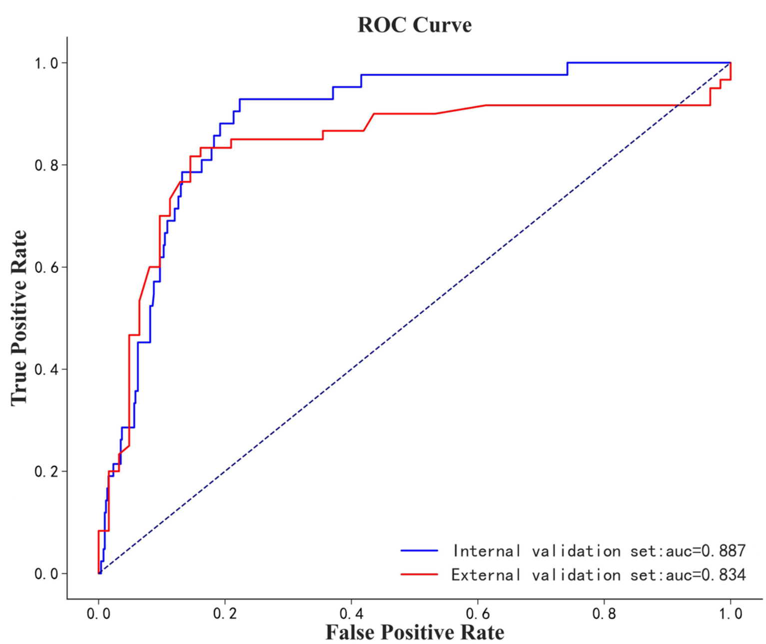

Fig. 4 Performance of RF model on the internal validation set and on the external validation set

RBC transfusion prior to surgery so that proper measures can be implemented to reduce the need for transfusion.

Several factors have been identified as being associated with perioperative RBC transfusion, such as age, fracture size, type of surgery, operative time, hypoproteinemia, preoperative Hb level, BMI, and intraoperative blood loss. Assaf et al [38]. identified noteworthy predictors for ABT within 72 h of admission in patients with hip fracture, including advanced age; lower hemoglobin on admission; female gender; type of surgical implant, and a shorter interval between admission and surgery with a regression algorithm. Bohl et al [16]. conducted a study that revealed a significant correlation between prolonged operative time and an increased risk of perioperative blood transfusion. Specifically, an increase in operative time by 15 min was found to increase the risk of transfusion by 9% [16]. Earlier research has also highlighted the significance of preoperative Hb levels as an essential

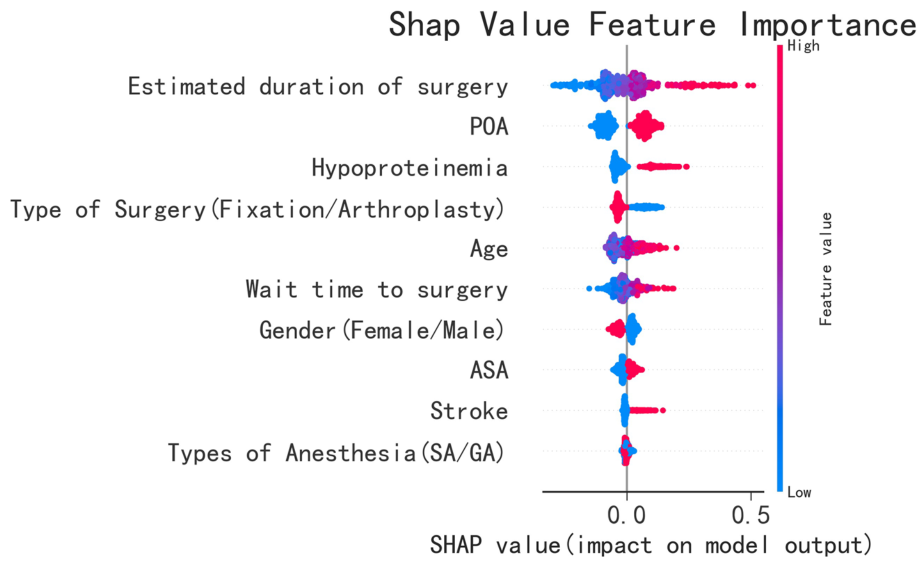

Fig. 5 Feature importance ranking based on Shapley Addictive exPlanations (SHAP) values in RF model

indicator for intraoperative blood transfusion. Wang et al. and Zhang *et al* [22, 23]. recently reported that age, fracture size, type of surgery, hypoproteinemia, preoperative Hb level, BMI, intraoperative blood loss were predictors for perioperative ABT in hip fracture patients. Base on the current findings, we built a RF model for prediction of intraoperative RBC transfusion in hip fracture patients. 10 preoperative variables were selected as significant factors using LASSO regression, including age, gender, POA, ASA, diabetes, history of stroke, hypoproteinemia, wait time to surgery, estimated duration of surgery, types of surgery. Notably, all these features can be explained by pathophysiology and clinical knowledge, which holds promise for clinical application in predicting sepsis for patients undergoing hip fracture surgery for intraoperative RBC transfusion.

RF is a commonly-used ML algorithm which combines the output of multiple decision trees to reach a single result. Besides, RF algorithm demonstrates robust adaptability to data, capable of handling both continuous and discrete variables without data normalization, thereby enhancing its suitability for assessing preoperative features. Within the context of this study, the RF model outperformed other models in predicting the need for intraoperative RBC transfusion in patients with hip fractures. Furtherly, SHAP analysis were used to indicate feature importance ranking in RF model. Longer estimated duration of surgery, POA, older age, hypoproteinemia and surgery of internal fixation were revealed by SHAP method the top 5 important variables contributing to intraoperative RBC transfusion.

The novelty of our study is developing a RF model with preoperative variables on prediction of RBC transfusion during hip fracture surgery and all 10 features in ML model were routinely recorded and easy to obtain. The prediction model developed in this study exhibited excellent discrimination. Moreover, a web page has been developed to facilitate the utilization of the model for the evaluation of RBC transfusion risks by clinicians. We have indeed developed an assessment tool that is simple and practical for clinical work. The orthopedic surgeon and anesthesiologist can evaluate probability of intraoperative RBC transfusion simply by typing in preoperative features so that preventive measures can be taken to reduce the need for RBC transfusions. These measures may include the administration of TXA and erythropoietin (EPO), as well as the utilization of intraoperative blood salvage and autologous blood transfusion. Such interventions have the potential to mitigate the negative clinical consequences associated with transfusion.

Limitations

There were several limitations in our study. First, given this is a retrospective analysis, we had to exclude a number of patients due to critical data missing, change of surgery schedule, and patients with undiagnosed comorbidities which inevitably caused selection bias and information bias. Second, clinicians might not have strictly followed the transfusion protocol due to the clinical complexity of each patient, including comorbidities, hemodynamic status, coagulation status of the patient, the bleeding risks of the procedure and even the same anesthesiologist may initiate different transfusion strategies

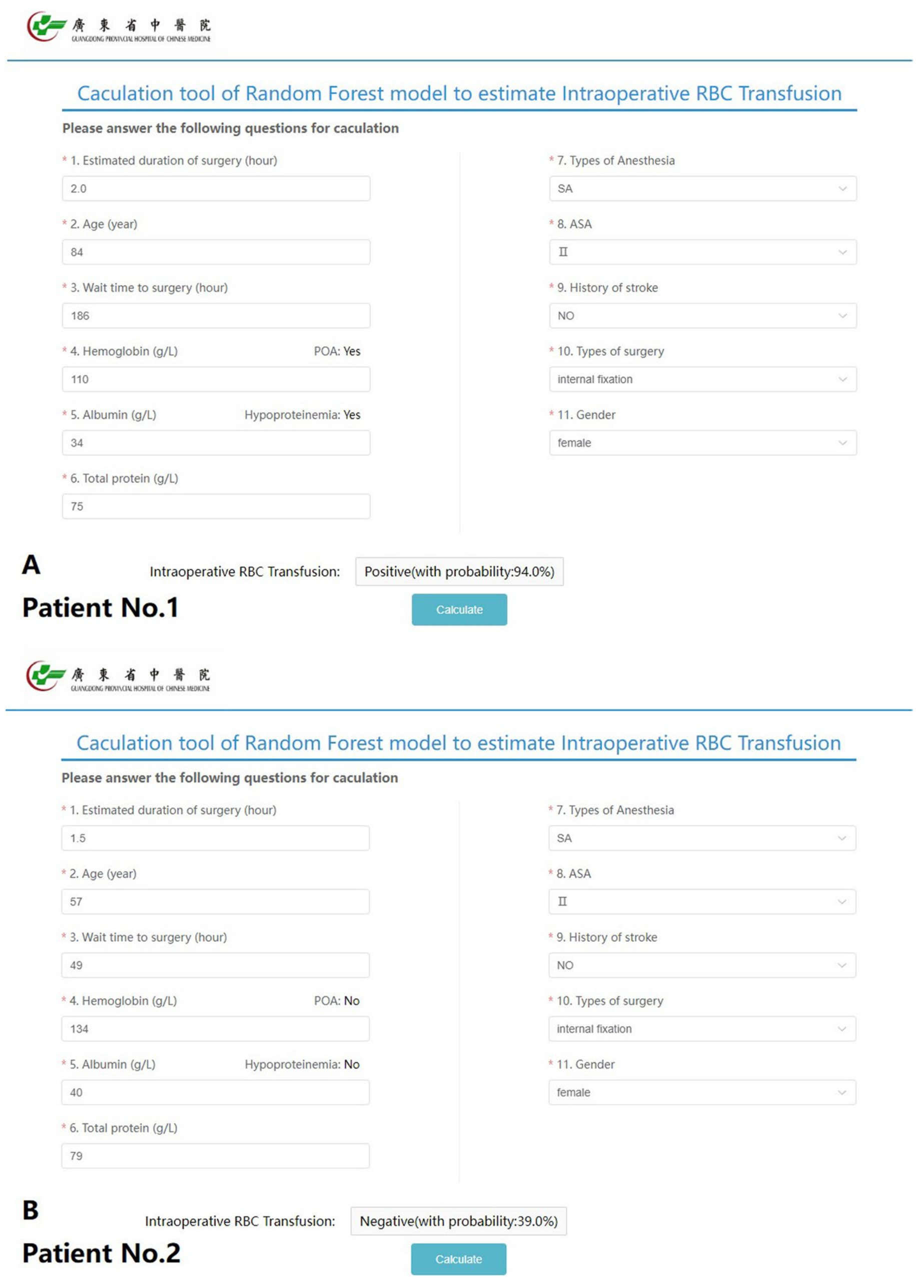

Fig. 6 Examples of website usage. Entering the input value determined the transfusion requirements and displayed how each value contributed to the prediction. **A** Patient No.1 needs RBC transfusion; **B** Patient No.2 does not need RBC transfusion

on different patients. Third, some patients might have received an RBC transfusion prior to surgery or received an autologous blood transfusion immediately after the procedure, which might compromise the effect of those variables on intraoperative RBC transfusion. Fourth, the study was externally validated with patient data from only one hospital, more data from other institutes were needed for further improvement of the model. Last but not least, the preoperative variables we assessed in the study were still limited which might cause confounding bias, and more patient characteristics should be included, such as frailty, kidney and liver function, type of fracture, and use of TXA, which might help make the predictive model more accurate.

Conclusion

In this study, we built an ML-based predictive model for RBC transfusion during hip fracture surgery, which exhibited satisfactory performance. The hip fracture patients were admitted to the hospital with distinct characteristics and comorbidities, we need tools to identify the patients at higher risk of RBC transfusion during surgery with preoperative characteristics. The predictive model is designed to reduce ABT during hip fracture surgery by identifying high-risk patients before surgery so that proper measures can be taken beforehand.

Glossary

RBC	Red blood cell
ABT	Allogenic blood transfusion
TXA	Tranexamic acid
Hb	Hemoglobin
ASA	Anesthesiologists physical status classification
GA	General anesthesia
SA	Spinal anesthesia
BMI	Body weight index
ML	Machine learning
AI	Artificial intelligence
DVT	Deep venous thrombosis
ALB	Albumin
TP	Total protein
POA	Preoperative anemia
LASSO	Least absolute shrinkage and selection operator
AUC	Area under the curve
ROC	Receiver operating characteristic
XGB	Extreme gradient boosting
GBDT	Gradient boosting decision tree
SVM	Support vector machine
MLP	Multi-layer perceptron
LR	Logistic regression
RF	Random forest
SHAP	SHapley Additive exPlanations
EPO	Erythropoietin

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12871-024-02832-y.

Additional file 1:

Acknowledgements
Not applicable.

Authors' contributions
The study was designed and conducted by YC-Z and GF-Z, with data collection carried out by WX-C, S-W and ZK-W. Y-D performed the necessary analytic calculations and statistical analysis. S-W also helped designed charts and figures presented in this article. The manuscript was authored by YC-Z, with guidance from CJ-C and QX-H in its improvement. All authors contributed valuable feedback and played a role in shaping the research, analysis, and manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The present study was a retrospective study, which did not interfere with hip fracture surgeries in any way. All of the clinical judgments were made by clinicians for medical reasons. No written consent was required in view of the purely observational nature of the study. No identifiable data of the patients were recorded during the whole study. The study was approved by the ethics committee of Guangdong Provincial Hospital of Chinese Medicine ((No. ZE2023-201–01).

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. Johnell O, Kanis JA. An estimate of the worldwide prevalence and disability associated with osteoporotic fractures. Osteoporos Int. 2006;17(12):1726–33.
2. Gruson KI, Aharonoff GB, Egol KA, Zuckerman JD, Koval KJ. The relationship between admission hemoglobin level and outcome after hip fracture. J Orthop Trauma. 2002;16(1):39–44.
3. Palm H, Hip Fracture: The choice of surgery. In: Falaschi P, Marsh D, editors. Orthogeriatrics: the management of older patients with fragility fractures. Cham (CH): Springer Copyright 2021, The Author(s); 2021. p. 125–41.
4. Bierbaum BE, Callaghan JJ, Galante JO, Rubash HE, Tooms RE, Welch RB. An analysis of blood management in patients having a total hip or knee arthroplasty. J Bone Joint Surg Am. 1999;81(1):2–10.
5. Spahn DJA. Anemia and patient blood management in hip and knee surgery: a systematic review of the literature. 2010;113(2):482–95.
6. Halm EA, Wang JJ, Boockvar K, Penrod J, Silberzweig SB, Magaziner J, Koval KJ, Siu AL. The effect of perioperative anemia on clinical and functional outcomes in patients with hip fracture. J Orthop Trauma. 2004;18(6):369–74.
7. Hagino T, Ochiai S, Sato E, Maekawa S, Wako M, Haro H. The relationship between anemia at admission and outcome in patients older than 60 years with hip fracture. J Orthop Traumatol. 2009;10(3):119–22.
8. Lee JH, Han SB. Patient blood management in hip replacement arthroplasty. Hip Pelvis. 2015;27(4):201–8.
9. Juraj M, Jaroslav V, Gažová A, Žufková V, Kyselovič J, Šteňo B. Evaluation of efficacy and safety of systemic and topical intra-articular administration of tranexamic acid in primary unilateral total hip arthroplasty. Medicine. 2021;100(26):e26565.
10. Jiang J, Xing F, Zhe M, Luo R, Xu J, Duan X, Xiang Z. Efficacy and safety of tranexamic acid for patients with intertrochanteric fractures treated with intramedullary fixation: A systematic review and meta-analysis of current evidence in randomized controlled trials. Front Pharmacol. 2022;13:945971.
11. Palmer AJR, Lloyd TD, Gibbs VN, Shah A, Dhiman P, Booth R, Murphy MF, Taylor AH, Kendrick BJL. collaborators, The role of intra-operative cell salvage in patient blood management for revision hip arthroplasty: a prospective cohort study. Anaesthesia. 2020;75(4):479–86.

12. Sperling JW, Duncan SF, Cofield RH, Schleck CD, Harmsen WS. Incidence and risk factors for blood transfusion in shoulder arthroplasty. J Shoulder Elbow Surg. 2005;14(6):599–601.
13. Gruson KI, Accousti KJ, Parsons BO, Pillai G, Flatow EL. Transfusion after shoulder arthroplasty: an analysis of rates and risk factors. J Shoulder Elbow Surg. 2009;18(2):225–30.
14. Ogbemudia AE, Yee SY, MacPherson GJ, Manson LM, Breusch SJ. Preoperative predictors for allogenic blood transfusion in hip and knee arthroplasty for rheumatoid arthritis. Arch Orthop Trauma Surg. 2013;133(9):1315–20.
15. Cao G, Huang Z, Huang Q, Zhang S, Xu B, Pei F. Incidence and risk factors for blood transfusion in simultaneous bilateral total joint arthroplasty: a multicenter retrospective study. J Arthroplasty. 2018;33(7):2087–91.
16. Bohl D, Ondeck N, Darrith B, Hannon C, Fillingham Y, Della Valle CJ. Impact of operative time on adverse events following primary total joint arthroplasty. J Arthroplasty. 2018;33(7):2256–2262.e4.
17. Desai SJ, Wood KS, Marsh J, Bryant D, Abdo H, Lawendy AR, Sanders DW. Factors affecting transfusion requirement after hip fracture: can we reduce the need for blood? Can J Surg J Can Chir. 2014;57(5):342–8.
18. Arshi A, Lai W, Iglesias B, McPherson E, Zeegen E, Stavrakis A, Sassoon A. Blood transfusion rates and predictors following geriatric hip fracture surgery. Hip Int. 2021;31(2):272–9.
19. Pedersen AB, Cronin Fenton D, Nørgaard M, Kristensen NR, Kuno Møller B, Erikstrup C. Body mass index, risk of allogeneic red blood cell transfusion, and mortality in elderly patients undergoing hip fracture surgery. Osteoporos Int. 2016;27(9):2765–75.
20. Bian FC, Cheng XK, An YS. Preoperative risk factors for postoperative blood transfusion after hip fracture surgery: establishment of a nomogram. J Orthop Surg Res. 2021;16(1):406.
21. Zhang Y, Yang D, Liu Z, Chen C, Ge M, Li X, Luo T, Wu Z, Shi C, Wang B, Huang X, Zhang X, Zhou S, Hei Z. An explainable supervised machine learning predictor of acute kidney injury after adult deceased donor liver transplantation. J Transl Med. 2021;19(1):321.
22. Haiying W, Xin Y, Yan F, Yan L, Cong W, Zhiwei L. Study of perioperative blood transfusion risk prediction model and verification for elderly patients with hip fracture. Beijing Mecial J. 2022;44(10):876–80,87.
23. Z., Z.; C., H.; Q., Z.; J., F. Construction of a nomogram model for prediction of allogeneic red blood cell transfusion during perioperative period in elderly hip fractures. Chin J Gerontol. 2022;42(24):5.
24. Organization WH. EN VMNIS - Indicators - Haemoglobin concentrations for the diagnosis of anaemia and assessment of severity. https://www.who.int/publications/i/item/WHO-NMH-NHD-MNM-11.1. Accessed 31 May 2011.
25. China, N. H. C. o. t. P. s. R. o. Guideline for perioperative patient blood management. http://www.nhc.gov.cn/wjw/s9493/202202/5e3bc1a664094da692bcb3e2e85efd34/files/93f67b893b634ca9be00020c08ce6ab4.pdf. Accessed 21 Jan 2022.
26. Jiang Y, Lin X, Wang Y, Li J, Wang G, Meng Y, Li M, Li Y, Luo Y, Gao Z, Yin P, Zhang L, Lyu H, Tang P. Preoperative Anemia and Risk of In-hospital Postoperative Complications in Patients with Hip Fracture. Clin Interv Aging. 2023;18:639–53.
27. Song K, Pan P, Yao Y, Jiang T, Jiang Q. The incidence and risk factors for allogenic blood transfusion in total knee and hip arthroplasty. J Orthop Surg Res. 2019;14(1):273.
28. Brunskill SJ, Millette SL, Shokoohi A, Pulford EC, Doree C, Murphy MF, Stanworth S. Red blood cell transfusion for people undergoing hip fracture surgery. Cochrane Database Syst Rev. 2015;2015(4):Cd009699.
29. Greenhalgh MS, Gowers BTV, Iyengar KP, Adam RF. Blood transfusions and hip fracture mortality - a retrospective cohort study. J Clin Orthop Trauma. 2021;21:101506.
30. Rasouli MR, Restrepo C, Maltenfort MG, Purtill JJ, Parvizi J. Risk factors for surgical site infection following total joint arthroplasty. J Bone Joint Surg Am. 2014;96(18):e158.
31. Raphael J, Hensley NB, Chow J, Parr KG, McNeil JS, Porter SB, Taneja M, Tanaka K, Mazzeffi M. Red blood cell transfusion and postoperative delirium in hip fracture surgery patients: a retrospective observational cohort study. Anesthesiol Res Pract. 2021;2021:8593257.
32. Foss NB, Kristensen MT, Kehlet H. Anaemia impedes functional mobility after hip fracture surgery. Age Ageing. 2008;37(2):173–8.
33. Gruson K, Aharonoff G, Egol K, Zuckerman J, Koval KJ. The relationship between admission hemoglobin level and outcome after hip fracture. J Orthop Trauma. 2002;16(1):39–44.
34. Spahn DR. Anemia and patient blood management in hip and knee surgery: a systematic review of the literature. Anesthesiology. 2010;113(2):482–95.
35. Karkouti K, Wijeysundera DN, Beattie WS. Risk associated with preoperative anemia in cardiac surgery: a multicenter cohort study. Circulation. 2008;117(4):478–84.
36. Lawrence VA, Silverstein JH, Cornell JE, Pederson T, Noveck H, Carson JL. Higher Hb level is associated with better early functional recovery after hip fracture repair. Transfusion. 2003;43(12):1717–22.
37. Jiang T, Song K, Yao Y, Pan P, Jiang Q. Perioperative allogenic blood transfusion increases the incidence of postoperative deep vein thrombosis in total knee and hip arthroplasty. J Orthop Surg Res. 2019;14(1):235.
38. Kadar A, Chechik O, Steinberg E, Reider E, Sternheim A. Predicting the need for blood transfusion in patients with hip fractures. Int Orthop. 2013;37(4):693–700.

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