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ORIGINAL RESEARCH

Predicting Postoperative Blood Transfusion in Elderly Patients Undergoing Total Hip and Knee Arthroplasty Using Machine Learning Models

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Purpose: With the aging population, the demand for total hip arthroplasty (THA) and total knee arthroplasty (TKA) has risen significantly. Elderly patients, especially those over 70 years, face a higher risk of perioperative bleeding and transfusion, increasing morbidity and mortality. Accurate transfusion risk prediction is vital for optimizing perioperative blood management. Traditional models often fail to capture complex factor interactions, whereas machine learning enhances predictive accuracy. This study aimed to develop predictive models for postoperative transfusion in elderly patients undergoing THA or TKA, identify key risk factors, and create an online prediction tool.

Patients and Methods: We retrospectively analyzed 1,520 elderly patients who underwent THA (659) or TKA (861). The Least Absolute Shrinkage and Selection Operator (LASSO) method was used for variable selection. The dataset was randomly split into training (70%) and testing (30%) sets. Five models—Logistic Regression (LR), Random Forest (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Naive Bayes (NB)—were developed and validated. Ten-fold cross-validation and grid search optimized model parameters. Model performance was evaluated using AUC, accuracy, precision, sensitivity, specificity, and F1 score. SHapley Additive exPlanations (SHAP) were applied to assess variable importance. An online tool was developed based on the models.

Results: Nineteen variables were retained. RF, LR, and SVM showed superior performance with AUC values exceeding 0.90. RF achieved the best results, with an accuracy of 0.86, precision of 0.80, specificity of 0.91, F1-score of 0.78, and sensitivity of 0.76. SHAP analysis highlighted intraoperative blood loss, hypertension, and postoperative drainage volume as major predictors.

Conclusion: The developed models and online tool support personalized transfusion risk assessment, optimizing perioperative management, optimizing blood utilization, and enhancing patient outcomes.

Keywords: elderly patients, total hip arthroplasty, total knee arthroplasty, blood transfusion, risk prediction models, online prediction tool

Introduction

With the aging population, degenerative joint diseases are becoming more prevalent. Total hip arthroplasty (THA) and total knee arthroplasty (TKA) are widely performed due to their success in treating end-stage joint diseases. With advancements in joint surgery techniques and materials, the number of these procedures has significantly increased each year. According to statistics from the American Joint Replacement Registry, the total number of primary joint replacements is projected to grow exponentially from 2020 to 2030.[1] THA and TKA can rapidly improve hip and knee joint function, but they are associated with significant blood loss during the perioperative period.[2] Consequently, blood transfusions are often necessary. However,

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perioperative transfusions can increase the risk of microcirculatory dysfunction and postoperative complications, such as deep vein thrombosis, surgical site infections, mortality, and transfusion-related acute lung injury.[3–6] Additionally, the direct and indirect costs of perioperative blood transfusions increase the financial burden on patients. Elderly patients, due to the decline in bodily functions and weakened hematopoietic capacity, have a significantly reduced ability to compensate for and tolerate acute blood loss. Moreover, they often have multiple comorbidities, making them more likely to require allogeneic blood transfusions and experience related complications during the perioperative period compared to the general population.[7–9] Compared to other types of surgeries, major orthopedic surgery (MOS) carries a higher risk of postoperative complications, and most patients undergoing these surgeries are elderly, typically aged 65 or older. Notably, being aged 70 or older is a high-risk factor for major bleeding after MOS,[10] which reported that among 1,048 patients, 56% underwent hip arthroplasty, and 53% were over 70 years old. Patients aged >70 years had a significantly increased risk of major bleeding (RR: 2.42 [95% CI: 1.54–3.81]), with relative risks of 2.61 (95% CI: 1.50–4.53) for hip arthroplasty and 2.25 (95% CI: 1.03–4.94) for knee arthroplasty. After multivariate analysis, age was found to be independently associated with a higher risk of major bleeding.

In the decision-making process for blood transfusions, assessing individual risks and benefits is increasingly emphasized. Pediatric guidelines have already been published, acknowledging the unique physiological needs of younger patients.[11] However, guidelines specifically for blood management in elderly patients are relatively rare. There is ongoing debate in clinical practice regarding whether elderly patients should follow a restrictive or liberal transfusion strategy. A liberal transfusion strategy (transfusing when hemoglobin levels are between 80 g/L and 100 g/L) considers factors such as anemia severity, cardiopulmonary function, age, and metabolic rate to determine the need for timely transfusion. In contrast, a restrictive transfusion strategy (transfusing when hemoglobin levels are below 80 g/L) involves strictly controlling the timing and amount of blood transfused to minimize the need for transfusions and reduce the risk of transfusion-related complications. A meta-analysis by Simon et al[8] of transfusion trials in elderly patients found that the hemoglobin threshold for patient blood management differs between elderly and younger patients. Elderly men require a hemoglobin level close to 100 g/L to have a reserve capacity similar to that of younger men with a hemoglobin level of 70 g/L. The changes in metabolism, heart, and lung function in the elderly reduce their tolerance to anemia. Increasing hemoglobin levels can improve oxygenation, and using a higher hemoglobin threshold for transfusions in elderly patients can lead to lower mortality rates, fewer cardiac complications, and better long-term outcomes. Furthermore, studies have found that a liberal transfusion strategy can reduce the long-term mortality risk for frail, anemic elderly patients with poor baseline conditions.[12] Conversely, Amin et al found that restrictive transfusion can achieve good perioperative outcomes and lower blood utilization in hemodynamically stable elderly patients.[13] In orthopedic perioperative care, there is still a high rate of inappropriate transfusions,[14,15] and the increased rate of allogeneic transfusions remains a major issue hindering patient functional recovery. In the context of global blood resource shortages and significant supply-demand imbalances in blood products, effective perioperative blood management for elderly patients is a pressing clinical need and a common goal for society. It is crucial to administer scientifically rational transfusions based on the patient's individual conditions and specific needs, which helps reduce postoperative complications, promote patient recovery, and save medical resources and costs. Therefore, it is essential to conduct research on transfusion management for the elderly population. By predicting transfusion risk in elderly patients based on their physical conditions and needs before surgery, clinical doctors can identify high-risk patients and take preventive measures selectively, making surgery safer and more effective.

Machine learning (ML) is a branch of artificial intelligence that derives patterns from data analysis and uses these patterns to predict unknown events or probabilities. It has shown good practicality and effectiveness in predicting and diagnosing clinical diseases.[16] Compared with traditional predictive models, machine learning can handle large amounts of variables with complex and nonlinear relationships, generating sophisticated predictive models with higher evaluation performance in analyzing big data medical issues. Currently, machine learning has been applied in various clinical aspects.[16–18]

Studies on postoperative blood transfusions after THA and TKA both domestically and internationally have generally focused on the entire patient population,[19,20] with few specifically targeting the elderly. In the study by Brian P. Chalmer et al,[20] a logistic regression (LR) generalized linear model was used to predict transfusions after TKA. However, LR assumes a linear relationship between predictors and outcomes, which may not fully capture the complex, nonlinear interactions among perioperative risk factors. Additionally, LR models are sensitive to multicollinearity and require careful handling of correlated variables to avoid biased estimates.[21] These limitations can reduce the predictive accuracy and generalizability of LR models when applied to complex clinical datasets. In contrast, machine learning methods can automatically model nonlinear relationships and interactions, making them more adaptable for predicting transfusion risk in diverse patient populations. Studies by Anirudh Buddhiraju et al[22] and Wayne Brian Cohen-Levy et al[23] on transfusions after initial THA analyzed a broad patient population without specific consideration for age-related differences. Due to variations in datasets and included variables, the factors significantly associated with transfusion rates varied. In contrast, our study focuses on elderly patients (≥60 years), providing a more targeted transfusion risk assessment tailored to this high-risk group.

Machine learning can effectively analyze the nonlinear relationships between risk factors in large datasets. However, due to its "black box" nature—relying on the complexity and multidimensionality of the algorithm structure to internalize data—its operations are not easily audited or understood by humans. SHAP (Shapley Additive ExPlanations) is a game-theoretic method that explains the output of any machine learning model. It uses the classical Shapley values from game theory and their related extensions to link optimal credit allocation with local explanations, visualizing individual and global decision processes in models. This solves the explainability problem in machine learning, aiding in the understanding of clinical and research outcomes.[24,25] Currently, there is a lack of explainability studies on predictive models for transfusions after THA and TKA.[26] Therefore, the aim of this study is to use machine learning algorithms to identify factors associated with blood transfusions in elderly patients after THA and TKA and to construct a predictive model. This will provide a theoretical basis for rational blood transfusion in elderly patients post-surgery. Finally, the model will be developed into an online platform to facilitate personalized transfusion risk assessment for elderly patients, providing a reference for clinical decision-making.

Materials and Methods

The data for this study were sourced from the medical records of elderly patients who underwent total hip arthroplasty (THA, n = 659) and total knee arthroplasty (TKA, n = 861) at the Second Hospital of Shanxi Medical University between January 2020 and July 2022. The inclusion criteria were as follows: patients aged ≥60 years, patients undergoing elective THA or TKA, and patients with complete medical records. The exclusion criteria were as follows: patients with bleeding disorders (such as thrombocytopenic disorders, purpura, hemophilia) or severe coagulopathy, and patients with malignant diseases or tumors.

This study was approved by the Ethics Committee of the Second Hospital of Shanxi Medical University (Approval No. (2023) YX (183)). The data used in this study were already de-identified before being made available for analysis to ensure privacy. Informed consent was waived by the Institutional Review Board due to the retrospective nature of the study. The study adhered to the principles of the Declaration of Helsinki and subsequent amendments.

Patient medical records were collected, and based on literature review and guidance from professional orthopedic clinicians, 29 initial variables related to postoperative transfusion were included in the analysis. These variables are: Age, Sex, Body Mass Index (BMI), Hypertension, Diabetes, History of cardiac disease, Peripheral vascular disease, Smoking history, Osteoporosis, Renal disease, History of stroke, Respiratory system disorders, Anemia, Preoperative hemoglobin levels, Preoperative hematocrit, Preoperative serum albumin, Preoperative creatinine levels, Hypoalbuminemia, Preoperative inferior vena cava surgery, American Society of Anesthesiologists (ASA) classification (I, II, III, IV), Anesthesia method (general, spinal, combined), Operation duration, Surgical type (unilateral, bilateral, revision), Tourniquet usage, Intraoperative blood loss, Tranexamic acid (TXA) usage, Drainage tube usage, Postoperative hospital stay, and Postoperative drainage volume. ASA classification was provided and carefully recorded by the anesthesiologist prior to surgery.

The dataset was randomly split into training and testing sets in a 7:3 ratio. The training set was used to develop models using five algorithms: logistic regression, random forest, support vector machine, k-nearest neighbors, and naive Bayes. The testing set was used to validate the model performance. Each model was constructed using ten-fold cross-validation and optimal parameters were selected via grid search. The models were then applied to the testing set and evaluated based on receiver operating characteristic curve (ROC) area under the curve (AUC), accuracy, precision, sensitivity, specificity, and F1 score. Additionally, SHAP (Shapley Additive Explanations) analysis was conducted on the predictive models to quantify the impact of each feature on the model predictions. This helps understand the overall model behavior and the relative importance of features, improving model interpretability. Finally, the predictive models were converted into a web-based application to predict transfusion risk based on inputted basic information and data. The overall development workflow is shown in Figure 1.

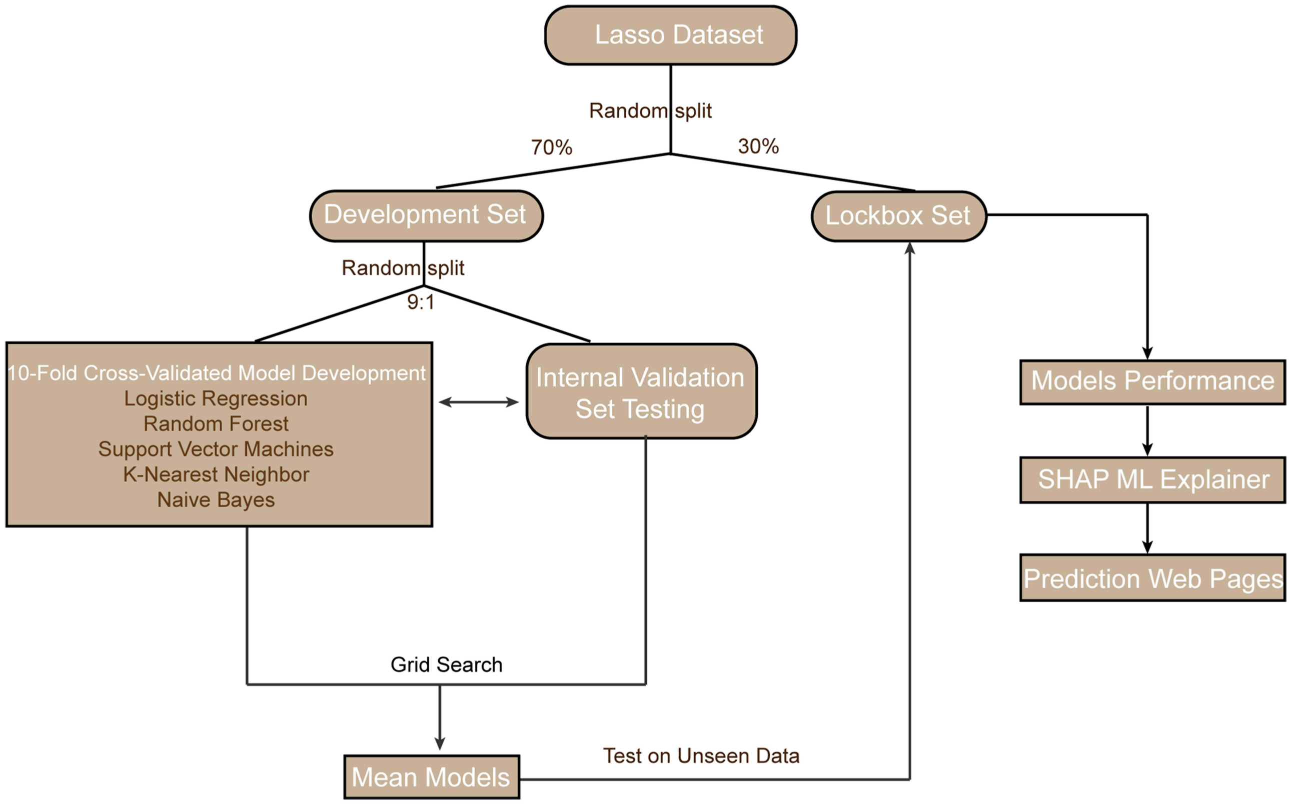

Figure 1 Flowchart of Developing ML-Based Predictive Models.

Other statistical methods included independent *t*-tests for continuous variables and chi-squared tests or Fisher's exact tests for categorical variables to assess differences between the transfusion and non-transfusion groups. All statistical analyses were performed using R (version 4.2.3) and Python (version 3.9.18).

Results

Basic Characteristics of the Dataset

A total of 1541 medical records were collected. After excluding 14 cases with coagulation disorders such as leukemia and thrombocytopenia and 7 cases of cancer patients, 1520 valid cases were included. Among these, 469 cases required transfusion, resulting in a transfusion rate of 30.8%. Within the valid cases, the THA dataset comprised 659 cases with a transfusion rate of 51.1%, and the TKA dataset comprised 861 cases with a transfusion rate of 15.3%. The overall demographic and perioperative factors of the patients are shown in Table 1, while the descriptive statistics for the THA and TKA datasets are shown in S1 and S2 Tables, respectively.

Selection of Study Variables

Using LASSO (Figure 2), the most relevant predictors of postoperative transfusion were identified. These factors include: age, sex, BMI, hypertension, diabetes, history of cardiac disease, peripheral vascular disease, smoking history, osteoporosis, renal disease, history of stroke, respiratory system disorders, hypoalbuminemia, preoperative hemoglobin levels, serum albumin levels, surgical type, tourniquet usage, intraoperative blood loss, and postoperative drainage volume. In the THA and TKA datasets, the variable selection results are shown in S1 and S2 Figures.

Performance Evaluation of Different Machine Learning Algorithms

Comparison of ROC curves for different algorithms in the total dataset (Figure 3), Figure 4 presents the ROC curves and AUC comparisons for different models, with (A) showing results from the THA dataset and (B) from the TKA dataset. as

Table 1 Demographic Characteristics and Perioperative Factors in the Total Dataset[a]

Variables	Total (n = 1520)	No Transfusion (n = 1051)	Transfusion (n = 469)	p-Value*
Age (years), Median (Q1, Q3)	68 (64, 72)	68 (64, 72)	68 (64, 72)	0.299
Sex, n (%)				0.898
Female	1032 (68)	712 (68)	320 (68)	
Male	488 (32)	339 (32)	149 (32)	
BMI (kg/m2), Median (Q1, Q3)	25.24 (22.72, 27.55)	25.56 (23.21, 27.77)	24.44 (21.98, 26.83)	< 0.001
Hypertension, n (%)				< 0.001
	1013 (67)	588 (56)	425 (91)	
Diabetes, n (%)				< 0.001
	353 (23)	194 (18)	159 (34)	
History of cardiac disease, n (%)				< 0.001
	136 (9)	60 (6)	76 (16)	
Peripheral vascular disease, n (%)				< 0.001
	157 (10)	82 (8)	75 (16)	
Smoking history, n (%)				< 0.001
	157 (10)	89 (8)	68 (14)	
Osteoporosis, n (%)				0.027
	125 (8)	75 (7)	50 (11)	
Renal disease, n (%)				< 0.001
	30 (2)	6 (1)	24 (5)	
History of stroke, n (%)				0.032
	75 (5)	43 (4)	32 (7)	
Respiratory system disorders, n (%)				< 0.001
	61 (4)	20 (2)	41 (9)	
Anaemia[b], n (%)				0.002
	71 (5)	37 (4)	34 (7)	
Hypoalbuminemia, n (%)				< 0.001
	15 (1)	2 (0)	13 (3)	
Preoperative hemoglobin levels, Median (Q1, Q3)	134 (125, 142)	135 (127, 143)	130 (118, 140)	< 0.001
Preoperative hematocrit levels, Median (Q1, Q3)	0.4 (0.38, 0.43)	0.41 (0.38, 0.43)	0.39 (0.36, 0.42)	< 0.001
Preoperative creatinine levels, Median (Q1, Q3)	58 (51, 68)	58 (51, 67)	59 (51, 70)	0.098
Preoperative serum albumin, Median (Q1, Q3)	39.6 (37.4, 41.8)	40.1 (37.9, 42.1)	38.6 (35.8, 41)	< 0.001
Preoperative inferior vena cava surgery, n (%)				0.274
	23 (2)	13 (1)	10 (2)	
Surgical type, n (%)				< 0.001
Unilateral	1410 (93)	1028 (98)	382 (81)	
Bilateral	87 (6)	21 (2)	66 (14)	
Revision	23 (2)	2 (0)	21 (4)	
Type of anesthesia, n (%)				< 0.001
General	99 (7)	63 (6)	36 (8)	
Spinal	327 (22)	194 (18)	133 (28)	
Combined	1094 (72)	794 (76)	300 (64)	
Tourniquet usage, n (%)				< 0.001
	861 (57)	729 (69)	132 (28)	
Intraoperative blood loss(mL), Median (Q1, Q3)	100 (37.5, 300)	50 (20, 100)	300 (50, 500)	< 0.001
Administration of TXA, n (%)				< 0.001
	1197 (79)	911 (87)	286 (61)	
Duration of surgery (min), Median (Q1, Q3)	89 (69, 111)	85 (69, 105)	98 (70, 125)	< 0.001
Drainage tube usage, n (%)				0.223
	1087 (72)	762 (73)	325 (69)	

(*Continued*)

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Table 1 (Continued).

Variables	Total (n = 1520)	No Transfusion (n = 1051)	Transfusion (n = 469)	p-Value*
Length of postoperative hospital stay (days), Median (Q1, Q3)	3 (3, 4)	3 (2, 4)	3 (3, 4)	< 0.001
ASA classification, n (%)				< 0.001
I	33 (2)	25 (2)	8 (2)	
II	1106 (73)	803 (76)	303 (65)	
III	361 (24)	218 (21)	143 (30)	
IV	20 (1)	5 (0)	15 (3)	
Postoperative drainage volume (mL), Median (Q1, Q3)	110 (0, 280)	105 (0, 250)	130 (0, 380)	0.006

Notes: *p-value calculated using independent *t*-test, Pearson chi-square test, or Fisher exact test. a Data are reported as Median (Q1, Q3) or number (%). b Anemia was defined as: male: Hb < 120 g/L; female: Hb < 115 g/L.
Abbreviations: BMI, body mass index; min, minute; TXA, tranexamic acid; ASA, American Society of Anesthesiologists.

well as model performance evaluation tables (Table 2), are shown in the text. Different algorithms exhibit varying predictive performances across the datasets. RF, LR, and SVM demonstrate superior classification performance across the total, THA, and TKA datasets, with all metrics (AUC, accuracy, precision, specificity, sensitivity, F1 score) exceeding 0.70 in both the total and THA datasets, particularly with AUC values surpassing 0.90. In the TKA dataset, these three algorithms show AUC values and accuracies above 0.90, highlighting their significant advantage in predicting post-operative blood transfusion risk for elderly patients.

RF outperforms all other algorithms across datasets. In the total dataset, RF achieves an AUC of 0.92, accuracy of 0.86, precision of 0.80, specificity of 0.91, F1 score of 0.78, and sensitivity of 0.76. In the THA dataset, RF's metrics are AUC 0.93, accuracy 0.87, precision 0.82, specificity 0.82, F1 score 0.88, and sensitivity 0.94. For the TKA dataset, RF shows AUC 0.91, accuracy 0.92, precision 0.84, specificity 0.98, F1 score 0.72, and sensitivity 0.63.

SVM matches RF in AUC, precision, and specificity for the total dataset but falls slightly short in other metrics. LR, while slightly behind RF and SVM, still shows good predictive capability. KNN and NB also perform well across various metrics, though they are less effective in F1 score and sensitivity.

Overall, RF, SVM, and LR exhibit excellent performance across datasets, with RF demonstrating the best overall performance in predicting postoperative transfusion risk in elderly patients. The results from this study indicate that the

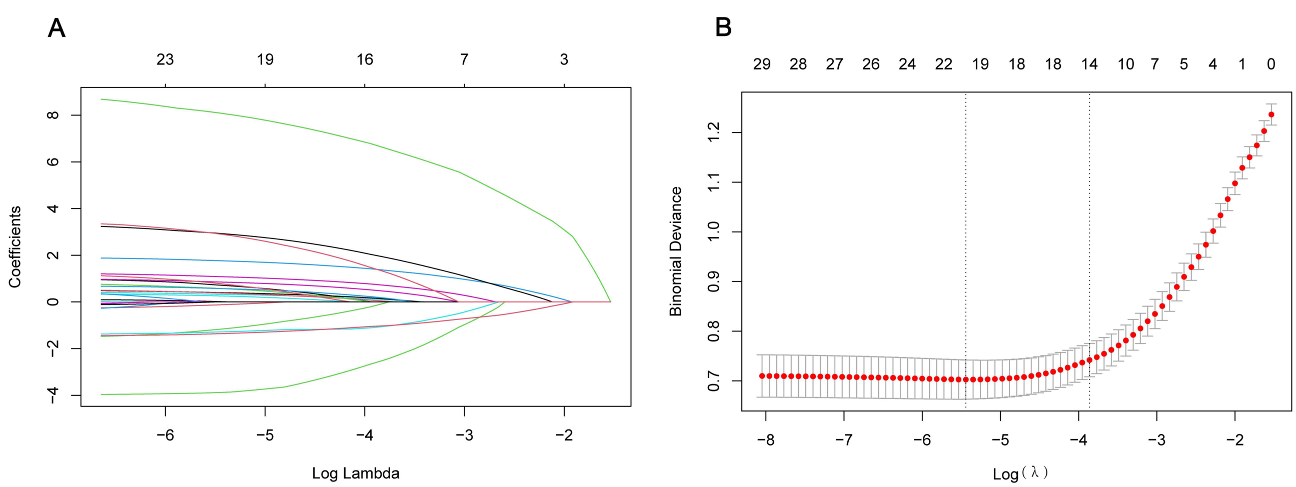

Figure 2 LASSO Variable Selection Path Diagram. (**A**) LASSO Variable Path Diagram. The horizontal axis represents the value of the regularization parameter λ, increasing from left to right. The vertical axis represents the coefficients of the variables. Each curve represents the path of a variable's coefficient as λ changes. (**B**) Cross-Validation Error Plot. This plot shows the relationship between log (λ) and the error, helping to observe the impact of λ changes on the error on a logarithmic scale. It is easier to identify the optimal λ value on this scale.

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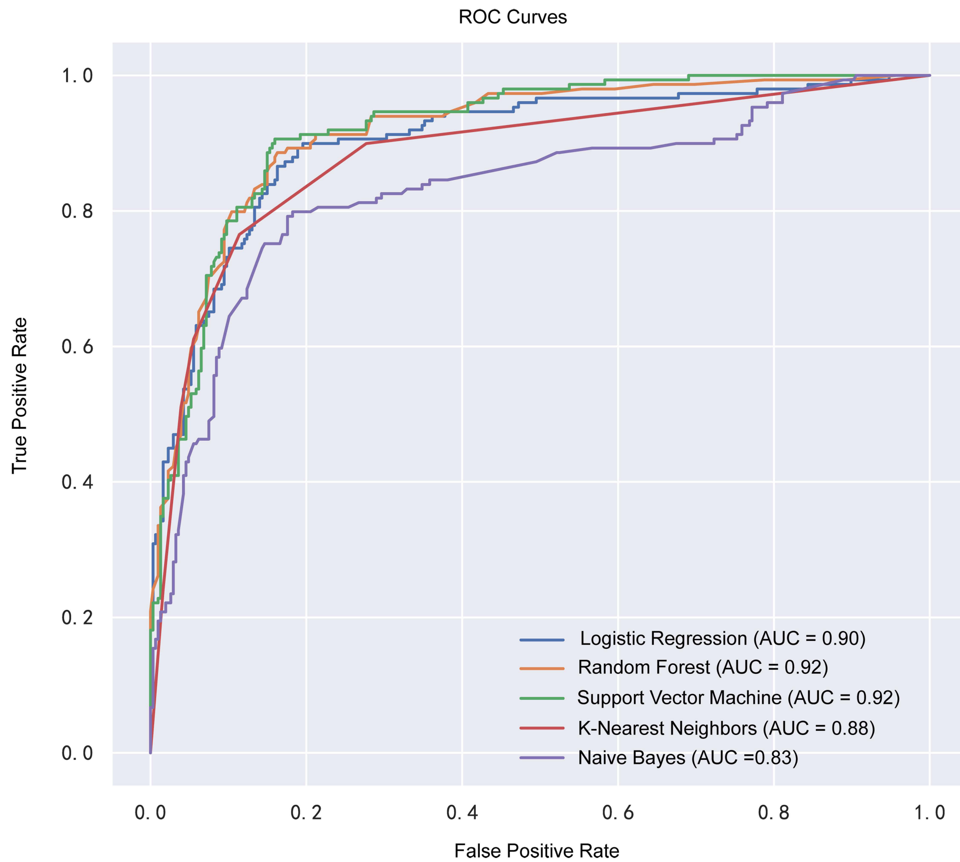

Figure 3 Comparison of Representative Subject Operating Characteristic (ROC) Curves in the Overall Dataset.

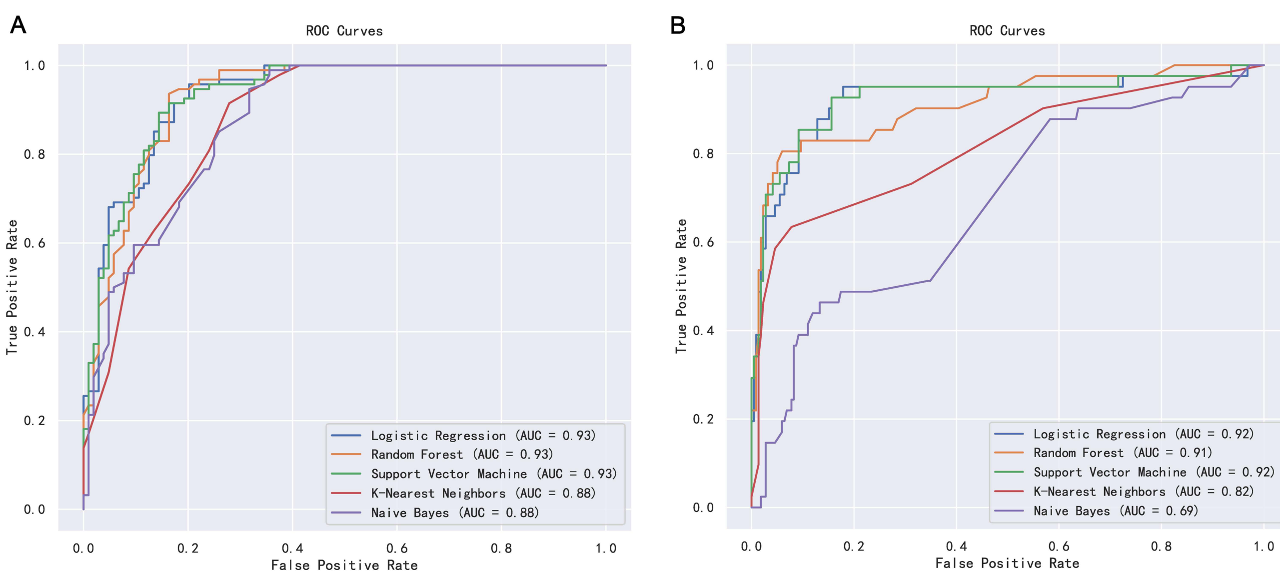

Figure 4 Comparison of Representative Subject Operating Characteristic (ROC) Curves in the THA and TKA Datasets. (**A**) The performance of different models in the THA dataset; (**B**) The performance of different models in the TKA dataset.

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Table 2 Performance of Different ML Algorithms in Predicting Postoperative Blood Transfusion in All Datasets*

Models	ROC AUC	Accuracy	Precision	Specificity	F1-Score	Sensitivity
(a) Performance of different machine learning algorithms in predicting postoperative blood transfusion in the total datasets.						
LR	0.90	0.84	0.78	0.90	0.75	0.72
RF	0.92	0.86	0.80	0.91	0.78	0.76
SVM	0.92	0.85	0.80	0.91	0.77	0.74
KNN	0.88	0.84	0.84	0.94	0.71	0.61
NB	0.83	0.81	0.77	0.92	0.66	0.58
(b) Performance of different machine learning algorithms in predicting postoperative blood transfusion in the THA datasets						
LR	0.93	0.86	0.81	0.80	0.87	0.94
RF	0.93	0.87	0.82	0.82	0.88	0.94
SVM	0.93	0.85	0.78	0.75	0.86	0.96
KNN	0.88	0.77	0.77	0.80	0.75	0.73
NB	0.88	0.79	0.75	0.74	0.80	0.85
(c) Performance of different machine learning algorithms in predicting postoperative blood transfusion in the TKA datasets.						
LR	0.92	0.91	0.80	0.97	0.68	0.59
RF	0.91	0.92	0.84	0.98	0.72	0.63
SVM	0.92	0.91	0.82	0.98	0.67	0.56
KNN	0.82	0.88	0.81	0.99	0.46	0.32
NB	0.69	0.83	0.17	0.98	0.04	0.02

Notes: * The datasets include the total datasets, the THA datasets and the TKA datasets.
Abbreviations: LR, logistic regression; RF, random forest; SVM, support vector machine; KNN, k-nearest neighbors; NB, naïve Bayes.

RF algorithm consistently provides stable and robust predictive performance across all datasets, offering valuable insights and support for future research and applications in predicting THA and TKA postoperative transfusion risks.

Contribution of Important Features to Model Prediction as Interpreted by SHAP

As established, RF demonstrates superior overall performance across datasets. Figure 5 shows the SHAP global dependency plot and SHAP mean absolute value, illustrating the importance rankings of variables in the RF model and their positive or negative effects on transfusion outcomes across datasets. The plots display feature rankings from top to bottom for (A-B) the total dataset, (C-D) the THA dataset, and (E-F) the TKA dataset, respectively.

In the total dataset, the top five important features are intraoperative blood loss, hypertension, drain usage, surgical type, and preoperative hemoglobin levels. In the THA dataset, the top five important features are hypertension, intraoperative blood loss, postoperative drainage volume, surgery duration, and preoperative hematocrit. In the TKA dataset, the top five important features are surgical type, intraoperative blood loss, postoperative drainage volume, preoperative hematocrit, and surgery duration.

Overall, the six features that most significantly impact prediction outcomes across the total, THA, and TKA datasets are intraoperative blood loss, hypertension, postoperative drainage volume, surgical type, surgery duration, and pre-operative hemoglobin.

Online Web Prediction

The developed models can be accessed for variable input and prediction on the following websites: (1) [https://thaweb-g7cn3xzdeqkgyecfvqi6ud.streamlit.app/], which predicts the risk of postoperative blood transfusion for THA patients; (2) [https://tkaweb-brwee2p63ldtrktgvcrspu.streamlit.app/], which predicts the risk of postoperative blood transfusion for TKA patients. The detailed page display is shown in Figure 6.

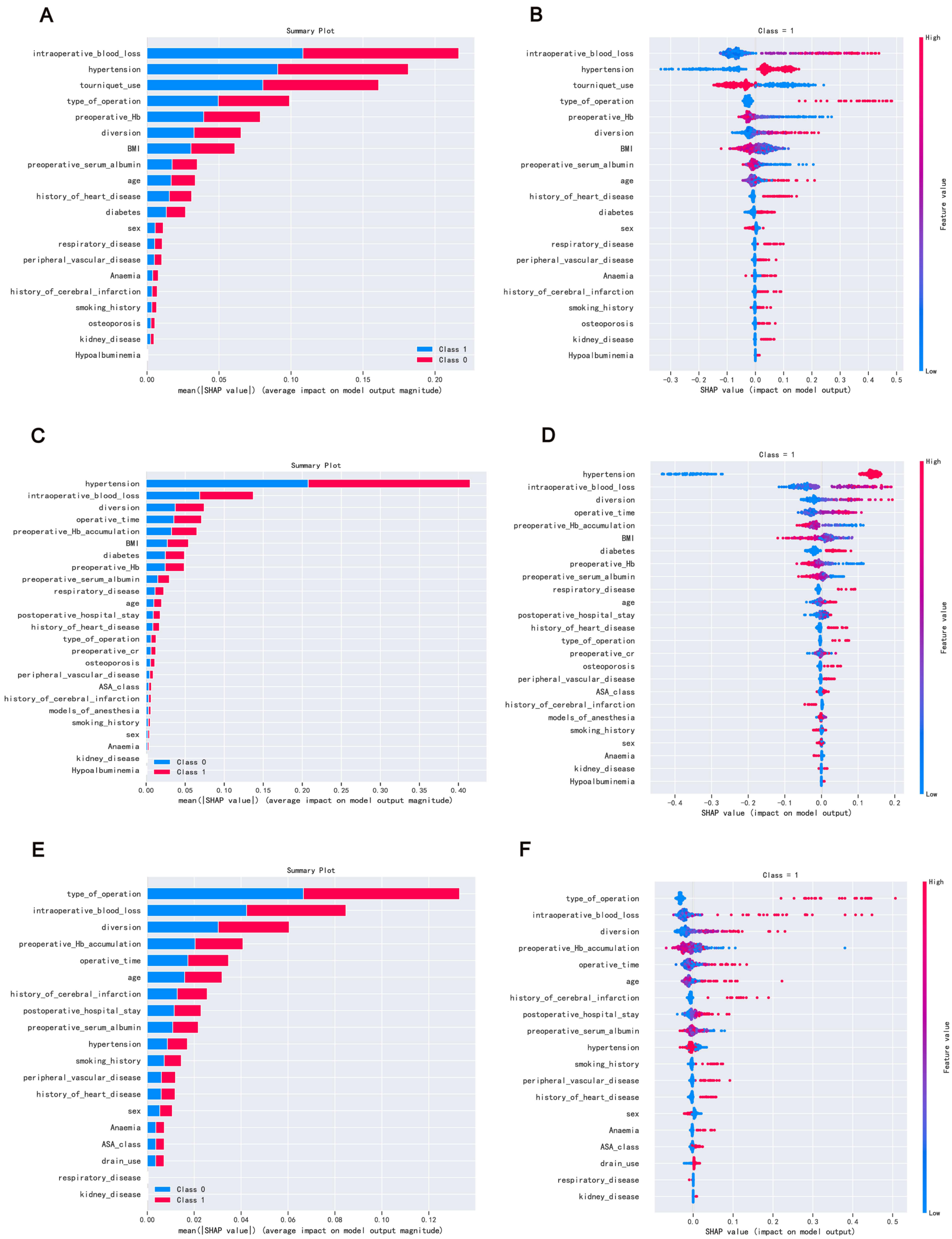

Figure 5 SHAP explains the contribution of important features to model predictions. (**A**) SHAP mean absolute value plot for the overall dataset; (**B**) SHAP global dependency plot for the overall dataset; (**C**) SHAP mean absolute value plot for the THA dataset; (**D**) SHAP global dependency plot for the THA dataset; (**E**) SHAP mean absolute value plot for the TKA dataset; (**F**) SHAP global dependency plot for the TKA dataset.

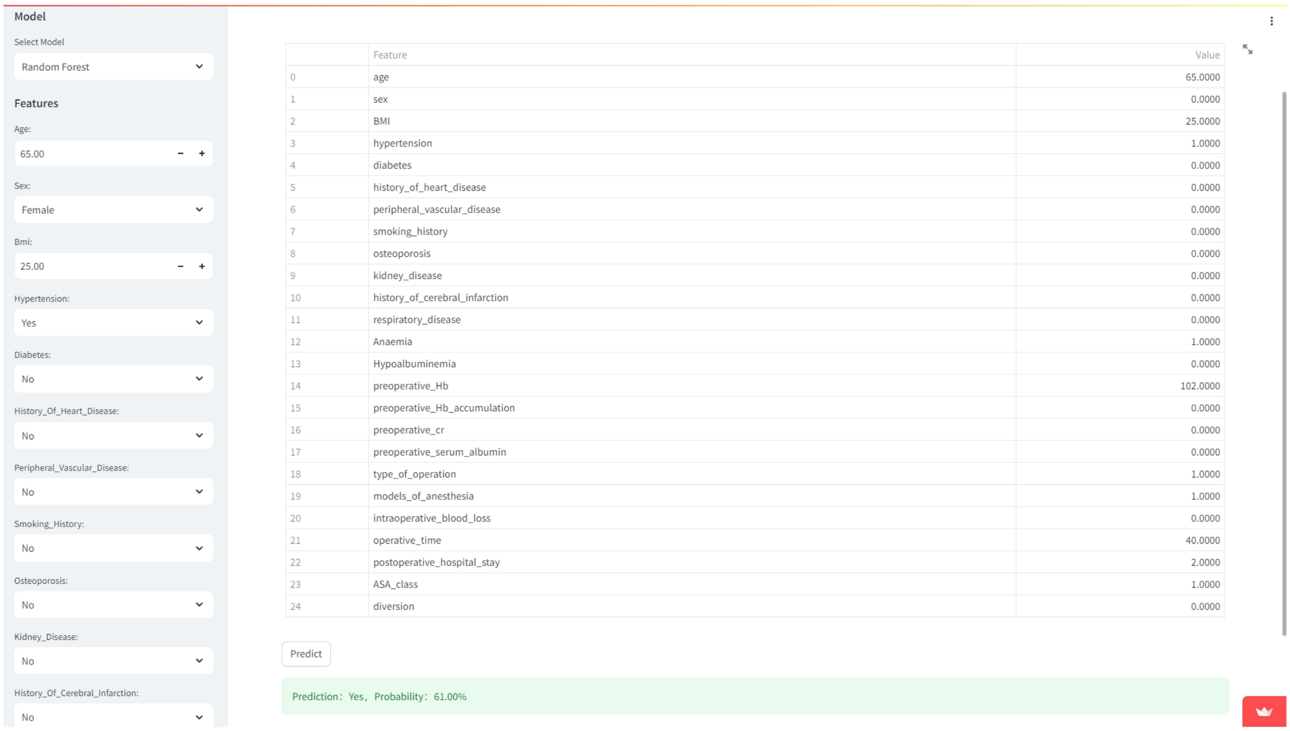

Figure 6 Example interface for predicting postoperative blood transfusion risk in patients.

Discussion

With the aging population, degenerative joint diseases are becoming increasingly common, leading to a significant annual increase in the number of THA and TKA procedures. These surgeries can result in substantial blood loss, and elderly patients, due to their declining physiological functions and underlying health conditions, are at a higher risk for blood transfusions and associated complications compared to the general population. This study developed prediction models for postoperative blood transfusion in elderly patients undergoing THA and TKA, identified relevant risk factors, and provided a convenient tool for personalized risk assessment. These models serve as a reference for clinical decision-making, facilitating scientific and rational blood transfusion judgments based on patients' individual conditions and needs, thereby offering a theoretical and scientific basis for blood management in elderly patients.

Among the evaluation metrics for model performance, the AUC value of each algorithm model provides an intuitive measure of classification capability. In the overall dataset, the random forest (RF) algorithm performed best with an AUC of 0.92, followed closely by the support vector machine (SVM) algorithm with an AUC of 0.92. The logistic regression (LR) algorithm had an AUC of 0.90, the k-nearest neighbors (KNN) algorithm had an AUC of 0.88, and the naive Bayes (NB) algorithm had the lowest AUC of 0.83. In the THA dataset, the random forest algorithm continued to excel. In the TKA dataset, the logistic regression and support vector machine algorithms both had high AUC values of 0.92, indicating their relatively strong performance, while the random forest algorithm followed closely with an AUC of 0.91. This indicates that the random forest algorithm has a strong ability to distinguish between positive and negative samples, making it one of the preferred models. Considering other metrics across different datasets, the random forest algorithm consistently outperformed other algorithms, demonstrating superior performance in predicting postoperative blood transfusion risk for THA and TKA.

Although other algorithms performed well on certain metrics, their overall performance still needs improvement. Factors contributing to the suboptimal performance of these algorithms may include insufficient model complexity, improper feature selection, sensitivity to data noise or outliers, and inherent limitations of the algorithms themselves. For instance, logistic regression is a linear classifier that is highly sensitive to the linear relationship between features and the target variable. If there are complex nonlinear relationships between features, logistic regression may fail to fit the data accurately.

In predicting postoperative blood transfusion risk for THA and TKA, the support vector machine (SVM) might focus excessively on local features while neglecting global ones if the feature dimension is high but the sample size is relatively small, leading to decreased performance. The K-nearest neighbors (KNN) algorithm's performance is influenced by distance measures and the number of neighbors. If there is noise or outliers in the feature space, KNN might be affected, resulting in poor performance when predicting postoperative blood transfusion risk. The naive Bayes algorithm assumes that features are independent of each other and that their influence on the target variable is also independent. If there is correlation between features or interaction effects on the target variable, the naive Bayes algorithm's performance may suffer. These limitations highlight the need for further research and discussion to enhance the performance of these algorithms.

This investigation systematically assesses the key factors influencing postoperative transfusion risk in elderly THA and TKA patients. SHAP analysis identified intraoperative blood loss, hypertension, surgical type, drainage tube usage, and preoperative hemoglobin levels as the most critical predictors across datasets.

Intraoperative blood loss has been reaffirmed by our analysis as a primary determinant of transfusion risk, aligning with clinical expectations and corroborated by previous studies. This finding highlights the critical need for effective intraoperative hemostatic measures, including the judicious use of tranexamic acid (TXA). Several studies have demonstrated that TXA significantly reduces intraoperative and postoperative blood loss without increasing thrombotic events.[27,28] Our study further supports the clinical importance of TXA in minimizing transfusion requirements among elderly patients.

Hypertension and cardiovascular considerations remain significant factors influencing transfusion risk, as evidenced by its predictive role in both the total dataset and the THA subgroup. Patients with hypertension may experience compromised vascular integrity, potentially leading to increased intraoperative bleeding and a higher likelihood of transfusion. Previous research has shown that maintaining a mean arterial pressure (MAP) between 60 and 70 mmHg during surgery can reduce blood loss without adversely affecting cerebral oxygenation or cognitive function.[26,29] Furthermore, intraoperative blood pressure management has been demonstrated to significantly mitigate both intraoperative and total blood loss[29,30,] emphasizing the need for optimized perioperative strategies in hypertensive elderly patients.

Drainage tube usage has also emerged as a key factor associated with transfusion risk. Studies suggest that the presence of drainage tubes may contribute to postoperative blood loss, thereby increasing transfusion rates.[27,31,32] In light of these findings, our study underscores the importance of individualized drainage strategies in elderly patients, aiming to balance postoperative drainage management with efforts to minimize transfusion risk.

Surgical type and procedural factors play a crucial role in determining transfusion requirements, particularly within the TKA dataset. Variations in soft tissue handling, surgical approach, and intraoperative hemostatic control contribute to differences in blood loss across procedures. Additionally, the surgeon's familiarity with vascular anatomy and intraoperative decision-making directly impacts transfusion needs, suggesting that personalized surgical planning is critical in elderly patients.

Unlike most studies that assess transfusion risk factors in general THA/TKA populations, our study focuses specifically on elderly patients (≥60 years), a demographic with distinct physiological challenges. Previous research has confirmed that patients aged ≥70 years are at significantly higher risk of major bleeding (RR: 2.42 [95% CI: 1.54–3.81]). Additionally, elderly patients have reduced compensatory capacity for anemia and may require higher transfusion thresholds compared to younger individuals.[8,33] Our study builds upon these findings by employing machine learning models to enhance transfusion risk prediction in elderly patients, providing individualized risk assessment beyond conventional statistical methods.

While our study comprehensively analyzed transfusion risk factors, certain variables suggested by previous studies—such as inflammatory markers (CRP, ESR, IL-6), blood conservation strategies (preoperative iron, erythropoietin, cell salvage), and additional surgical factors (approach, intraoperative complications)—were not included in our final models. These variables, while potentially relevant, were not consistently available in routine clinical records and thus were not incorporated to ensure model practicality. Future studies incorporating these factors could further refine transfusion risk prediction.

Effective transfusion management requires balancing patient safety with healthcare resource utilization. The developed predictive models provide a valuable tool for personalized transfusion risk assessment in elderly patients undergoing THA and TKA, which may facilitate more precise perioperative blood management. Previous studies[34] have highlighted that patient blood management (PBM) strategies, including optimizing transfusion practices, can contribute to improved patient outcomes and healthcare resource optimization. Effective PBM has been associated with reduced hospital stays, lower healthcare expenditures, and decreased transfusion-related complications, further emphasizing the importance of integrating predictive models into perioperative management.

While our study did not conduct a formal cost-benefit analysis, the potential of ML-based prediction models in reducing unnecessary transfusions and improving blood utilization efficiency is noteworthy. By enabling early identification of high-risk patients, these models could help guide preoperative preparation, reduce excessive blood transfusions, and optimize blood resource allocation, thereby contributing to improved patient outcomes and cost-effective healthcare management. However, a comprehensive cost-effectiveness analysis is necessary to further validate the economic benefits of implementing such predictive models in real-world clinical settings. Future studies should incorporate economic assessments to quantify the impact of ML-driven transfusion strategies on healthcare costs and patient outcomes.

In summary, analyzing key features helps to better understand the factors affecting postoperative transfusion risk in elderly THA and TKA patients and provides guidance for clinical practice. Timely monitoring and control of intraoperative blood loss, management of hypertension, rational use of drainage tubes, and personalized management strategies for different types of surgery can help reduce the risk of postoperative transfusion in elderly patients, improving clinical outcomes. The constructed prediction models and online prediction tools enable clinicians to perform personalized transfusion risk assessments for elderly patients. This personalized assessment, which takes into account specific patient characteristics and surgical details, can more accurately predict postoperative transfusion risk, providing an important reference for clinical decision-making and aiding clinicians in developing individualized treatment plans. Based on the prediction results, doctors can timely assess transfusion risks and implement effective interventions, thereby reducing the need for postoperative transfusion, minimizing the risk of transfusion-related complications, improving treatment outcomes, and aiding in patient recovery. Rationalizing transfusion practices can save medical resources and costs to some extent, potentially reducing unnecessary tests for patients, alleviating the economic burden on society and patient families, and minimizing the side effects caused by diagnostic tools. The application of prediction models and online prediction tools promotes the scientific and standardized nature of clinical decision-making. Doctors can use objective data and model prediction results to develop more scientific and reasonable treatment plans, improving the efficiency and quality of clinical work. In the context of blood resource shortages and high rates of inappropriate transfusions, scientific and reasonable transfusion judgments based on patients' conditions and specific needs provide a theoretical basis and scientific foundation for blood management in elderly patients. Finally, the machine learning-based approach of this study, capable of handling large-scale datasets and high-dimensional data, lays the foundation for future expansion to larger datasets and more variables, thus providing greater development potential for research on rational transfusion in elderly patients.

In conclusion, the prediction model and online prediction tools hold significant clinical application and importance in the postoperative transfusion management of elderly THA and TKA patients. Rather than defining new transfusion thresholds, our model is designed to complement existing clinical guidelines by identifying high-risk patients preoperatively and supporting evidence-based transfusion decisions. While hemoglobin levels are a crucial reference indicator for determining the need for red blood cell transfusion, clinical practice should comprehensively consider the patient's comorbidities, vital signs, and other factors to analyze the specific situation. Advocating for rational blood use can save blood products and reduce adverse reactions, ultimately benefiting the patient.

Future research should focus on validating these models in multicenter cohorts to improve their generalizability and clinical applicability. Expanding feature selection to incorporate additional relevant variables, such as inflammatory markers and advanced blood conservation strategies, may further enhance predictive performance. Given the potential advantages of advanced ensemble learning methods, future studies could explore the application of XGBoost and LightGBM to optimize the bias-variance trade-off. Additionally, prospective validation in real-world clinical settings will be essential to assess the practical impact of these models on transfusion practices, healthcare efficiency, and patient outcomes.

However, this study has certain limitations. The data used in this research were sourced from the medical records of elderly patients at a single hospital, making it a single-center study. This may limit the representativeness of the sample, affecting the model's generalizability and external validity. Differences in surgical techniques, transfusion thresholds, and perioperative management strategies across regions may impact model performance. Additionally, while our study incorporated key transfusion risk factors, certain perioperative variables (eg, inflammatory markers, advanced blood conservation strategies) were not included, which could further refine risk prediction models. Future research could improve the predictive accuracy and stability of the model by incorporating more clinical data and utilizing more advanced artificial intelligence techniques.

Conclusions

By developing a predictive model, this study provides an in-depth analysis of postoperative transfusion risk specifically in elderly patients undergoing total hip arthroplasty (THA) and total knee arthroplasty (TKA). Our findings demonstrate that the random forest (RF) model achieves the highest predictive performance, with AUC values exceeding 0.90 in both THA and TKA datasets, supporting its reliability in transfusion risk assessment for these surgical populations.

SHAP analysis identified key risk factors, including intraoperative blood loss, hypertension, and postoperative drainage volume, which have significant implications for perioperative transfusion decision-making in elderly patients. These findings reinforce the necessity of preoperative optimization and intraoperative hemostatic strategies to mitigate transfusion risks in this high-risk group.

This study contributes to the personalized transfusion management of elderly THA and TKA patients, offering a data-driven approach to support individualized perioperative planning. By incorporating advanced feature selection techniques and explainable machine learning methods, our model enhances clinical interpretability and usability, distinguishing it from previous transfusion prediction models.

Additionally, an online prediction tool was developed to facilitate real-time, patient-specific transfusion risk estimation, allowing clinicians to make informed decisions regarding transfusion strategies. This tool may help optimize blood product utilization, minimize unnecessary transfusions, and reduce associated complications in elderly surgical patients.

Moving forward, multicenter validation studies are necessary to confirm the external applicability of the model across diverse populations. Further refinement of the model by integrating additional predictive factors, such as inflammatory markers and blood conservation strategies, could further enhance its predictive performance and clinical utility.

In conclusion, this study provides a valuable framework for optimizing transfusion strategies in elderly THA and TKA patients, with potential implications for improving patient outcomes and perioperative blood management.

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Disclosure

The authors report no conflicts of interest in this work.

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