Article

Factors Associated With Intraoperative Acquired Pressure Injury in Total Knee Arthroplasty Patients: Development of Predictive Models

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AIM: To construct and validate a risk prediction model for intraoperatively acquired pressure injury (IAPI) in total knee arthroplasty (TKA), thereby improving the accuracy of early diagnosis and intervention.

METHODS: This retrospective study included 546 patients who underwent elective total knee arthroplasty at from Chengdu 363 Hospital Affiliated to Southwest Medical University and Chengfei Hospital. According to predefined inclusion and exclusion criteria, 278 cases from Chengdu 363 Hospital Affiliated to Southwest Medical University between January 2022 and December 2023 were used as the training set, while 118 cases from 2024 served as the internal validation set; 150 cases from Chengfei Hospital in 2024 were used as the external validation set. Feature variables were screened using multivariable logistic regression and Lasso regression analyses. Sensitivity, specificity, accuracy, F1-score (F1), and area under the curve (AUC) were used to evaluate discriminative performance. External validation was performed using AUC to evaluate generalizability. The optimal model was further interpreted by the Shapley additive explanation (SHAP) method to identify key risk factors.

RESULTS: Among the four machine learning algorithms tested, the gradient boosting decision tree (GBDT) model demonstrated the best discriminative performance (AUC 0.867, sensitivity 0.725, specificity 0.836, accuracy 0.788, and F1 value 0.747). The five most influential variables associated with IAPI risk were body mass index (BMI), Braden score, age, American Society of Anesthesiologists (ASA) classification, and surgical duration.

CONCLUSIONS: The GBDT-based prediction model, combined with the SHAP interpretation, effectively identifies risk factors for intraoperative IAPI in TKA. This model provides strong support for early clinical intervention and contributes to improving the outcomes of IAPI care.

Keywords: total knee arthroplasty; intraoperatively acquired pressure injury; machine learning; prediction model; risk factors

Introduction

Total knee arthroplasty (TKA) is the standard treatment for end-stage knee osteoarthritis, effectively relieving pain, restoring joint function, and significantly improving the quality of life for patients. However, intraoperatively acquired pressure injury (IAPI) is a common complication that significantly influences surgical outcomes and recovery [1]. According to the international National Pressure Ulcer Advisory Panel/European Pressure Ulcer Advisory Panel (NPUAP/EPUAP) classification system [2], IAPIs are divided into six categories: Stage I (non-blanchable erythema), Stage II (partial-thickness skin damage with blister formation), Stage III (full-thickness skin loss), Stage IV (full-thickness tissue loss), unclassifiable (wound obscured by eschar), and deep tissue damage (localized purple or brownish-red discoloration). Among TKA patients, Stage I (60%–75%) and deep tissue damage (20%–30%) are the most frequently observed types [3,4]. Reported incidence rates of IAPI range widely from 4.9% to 66.0% [5,6], with elderly, obese, and comorbid patients (e.g., those with diabetes) being particularly susceptible. The occurrence of IAPI not only increases the risk of infection but also prolongs hospitalization, raises medical costs, and adversely affects prognosis and patient-physician relationships.

Conventional IAPI prediction methods have significant limitations. Retrospective analyses of risk factors (e.g., age, body mass index (BMI), duration of surgery) [7,8] struggle to develop personalized prediction tools. Generic risk assessment scales such as Bergstrom [9] and Waterlow [10] fail to account for surgical-specific factors (e.g., tourniquet use, fixed positioning) and often lack sufficient sensitivity and specificity [11]. Although some studies have applied statistical models or preliminary machine learning approaches [12,13], their predictive performance remains limited with respect to feature depth, non-linear relationships, and generalizability to the TKA population.

Given the clinical limitations of acquiring dynamic indicators, this study emphasized readily available preoperative

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baseline characteristics and surgery-related static parameters. Machine learning (ML), with its superior capabilities in high-dimensional data processing, complex pattern recognition, and non-linear relationship modeling, offers a promising approach to integrate these static variables and construct more precise predictive models. Therefore, this study aimed to identify risk factors for IAPI in TKA patients and to develop a machine learning-based prediction model using only static variables. The ultimate goal was to provide a practical tool for identifying high-risk patients preoperatively and immediately postoperatively, thereby enabling targeted nursing interventions such as enhanced protection and early decompression to reduce IAPI incidence, improve patient outcomes, and elevate the quality of perioperative care.

Methods

Clinical Data

This retrospective study included 546 patients who underwent elective total knee arthroplasty at Chengdu 363 Hospital Affiliated to Southwest Medical University and Chengfei Hospital. Based on inclusion and exclusion criteria, 278 patients who underwent elective total knee arthroplasty at Chengdu 363 Hospital Affiliated to Southwest Medical University between January 2022 and December 2023 comprised the training set. A total of 118 patients treated at Chengdu 363 Hospital Affiliated to Southwest Medical University in 2024 were used as the internal validation set, while 150 patients who underwent elective total knee arthroplasty at Chengfei Hospital from January to December 2024 served as the external validation set.

Inclusion criteria: (1) age ≥18 years, meeting the surgical indications for total knee arthroplasty relevant contraindications; (2) single-knee pathology undergoing first-time surgical treatment; (3) preoperative intact skin with no existing pressure injuries in any part of the body; and (4) no cognitive or communication disorders.

Exclusion criteria: (1) presence of pressure injury at the time of admission; (2) dermatologic conditions interfering with skin evaluation (e.g., psoriasis, eczema, contact dermatitis, vitiligo); and (3) severe cardiac, hepatic, or renal dysfunction, or severe infectious diseases.

This study was approved by the Medical Ethics Review Committee of Chengdu 363 Hospital Affiliated to Southwest Medical University (Ethical Number: 2024-069), and all patients provided written informed consent.

The TKA patient selection flowchart is shown in Fig. 1.

Observation Indices

Clinical data were collected for each patient, including gender, age, BMI, underlying comorbidities, duration of surgery, intraoperative hypothermia, intraoperative blood loss, tourniquet application time, American Society of Anesthesiologists (ASA) classification, Braden score, and preoperative psychological status assessment [14,15].

Relevant Definitions

The diagnosis and staging of IAPI followed the standards outlined in the 2019 International Clinical Practice Guidelines for the Prevention and Treatment of Pressure Injuries/Ulcers [2]. IAPI was defined as tissue damage that occurs within 48 to 72 hours postoperatively at the surgical pressure site, caused by intraoperative pressure or shear force. Assessment and confirmation were conducted independently by two senior wound ostomy therapists, with disagreements resolved by a third expert.

In this study, any red rash that did not blanch under pressure (Stage I injury) or more severe injuries (Stage II or higher) was considered an IAPI event. The Braden score, which evaluates six dimensions: sensory perception, humidity, activity, mobility, nutrition, and friction/shear, was used to comprehensively determine the risk of pressure ulcers. Friction/shear scores range from 1 to 3, while the remaining items range from 1 to 4, yielding a maximum score of 23. Higher scores indicate lower risk of pressure injury, with a score ≥18 denoting low risk of pressure injury.

Psychological status was assessed using the self-rating anxiety scale (SAS) and self-rating depression scale (SDS). Each scale includes 20 items scored on a 4-point scale, with total scores ranging from 20 to 80 points. The cutoff values were 50 points for SAS and 53 points for SDS. Higher scores indicate more severe anxiety or depression symptoms.

Intraoperative hypothermia was defined as a minimum core body temperature of <36 °C during surgery. Intraoperative blood loss (mL) was calculated as:

Blood loss = volume in collection bottle (mL) + blood volume absorbed by gauze (mL) – irrigation fluid (mL).

Estimated blood absorption capacity of gauze: a fully saturated 4×4 gauze $\approx$ 10 mL; a fully saturated large gauze (30×30 cm) $\approx$ 50 mL of blood [16].

Variable Screening, Machine Learning Algorithms, and Model Building

A two-stage variable selection strategy was applied to optimize model performance and reduce overfitting. First, features not significantly associated with IAPI were excluded by univariate analysis ($p < 0.05$). Subsequently, Lasso regression (with 10-fold cross-validation to select the optimal λ parameter) was employed to address multicollinearity among variables, compressing coefficients of less relevant variables to zero through a penalty mechanism, and retaining the variables most relevant for predicting IAPI. Finally, variables with non-zero coefficients identified by Lasso regression were used as input features for models: logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), and gradient boosting decision tree (GBDT). The discriminative performance of each model was evaluated and compared using sensitivity, specificity, accuracy, F1-score (F1), and area under the curve (AUC) in the validation set to identify the optimal predictive model.

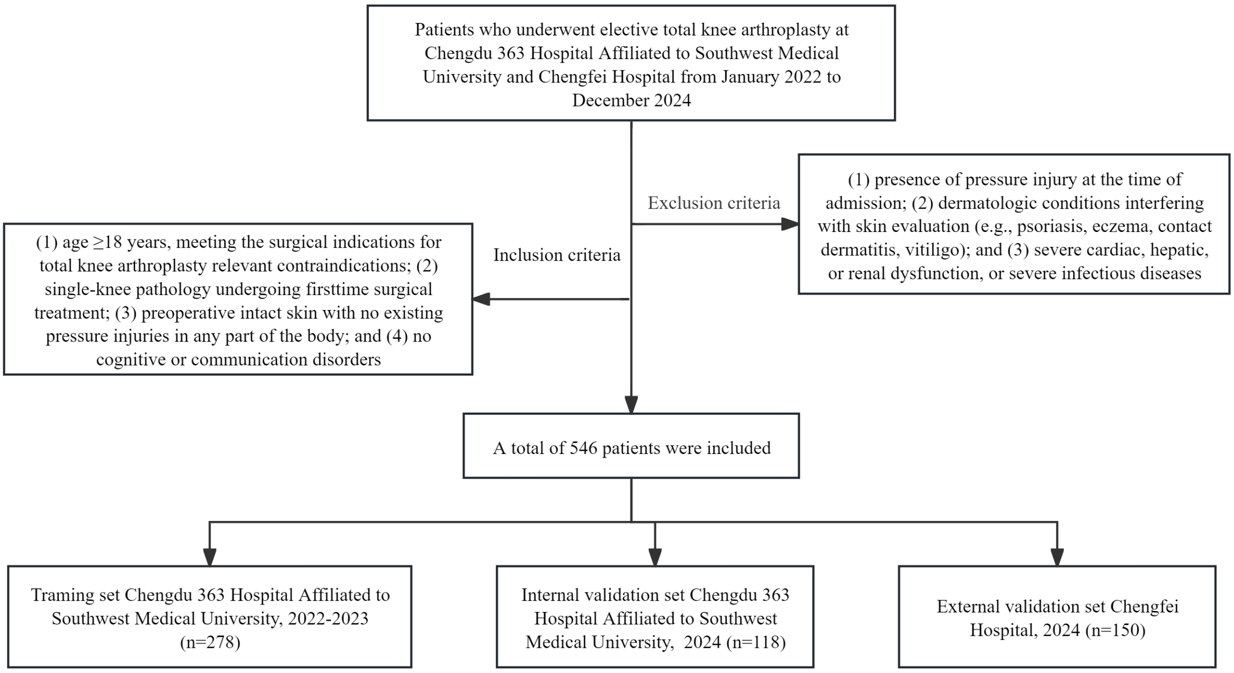

Fig. 1. Flowchart of patient selection for total knee arthroplasty (TKA).

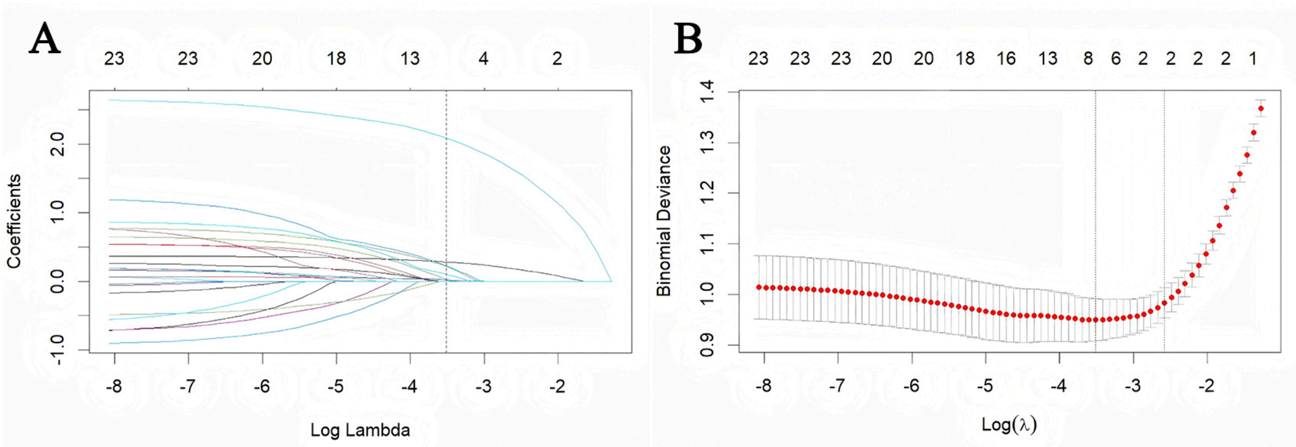

Fig. 2. Lasso regression coefficient profiles for predictors of IAPI. (A) Path of Lasso regression coefficients with varying values of the tuning parameter λ. (B) Binomial deviance trajectory plot used to determine the optimal λ for model selection. IAPI, intraoperatively acquired pressure injury.

External validation of the optimal model was performed using AUC to assess generalizability. The Shapley additive explanation (SHAP) method was further applied to interpret the contribution of each feature variable to the final predictive model.

Statistical Analysis

Data were statistically analyzed and a model was constructed using SPSS version 27 (manufacturer: IBM) and R version 4.4.3 software (manufacturer: The R Foundation). Continuous variables with a normal distribution were expressed as mean $\pm$ standard deviation ($\bar{x} \pm$ s), and comparisons between two groups were performed using independent-samples *t*-tests. Non-normally distributed variables were expressed as median (Q1, Q3), and comparisons between two groups were performed using the Mann-Whitney U test. Categorical variables were expressed as frequencies and percentages (n, %) and analyzed using the chi-square test.

Lasso regression analysis was applied to screen characteristic variables with IAPI as the dependent outcome. Receiver operating characteristic (ROC) curves were generated for each model identifying IAPI in the validation set, and the corresponding area under the curve values were calculated

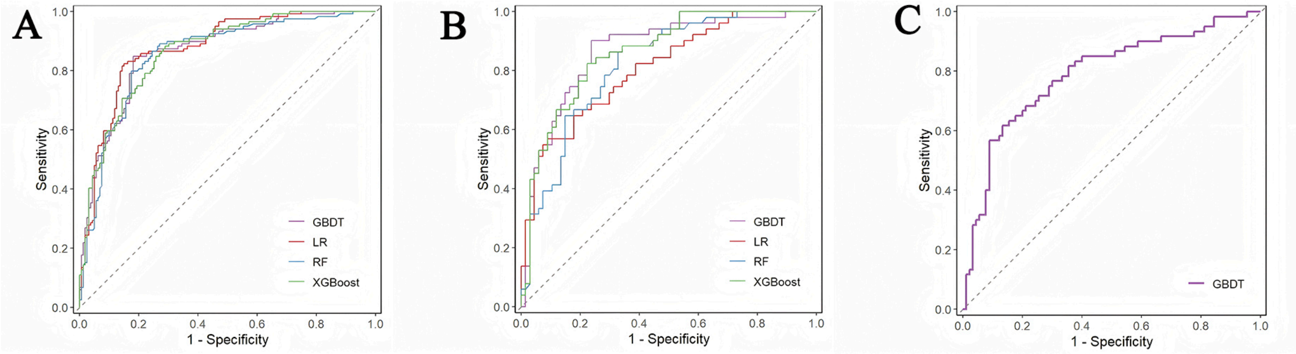

Fig. 3. Receiver operating characteristic (ROC) curves of four machine learning models for predicting IAPI in TKA patients. (A) Training set, Chengdu 363 Hospital Affiliated to Southwest Medical University (January 2022–December 2023). (B) Internal validation set, Chengdu 363 Hospital Affiliated to Southwest Medical University (January 2024–December 2024). (C) External validation set, Chengfei Hospital (January 2024–December 2024).

and compared. A two-tailed p-value < 0.05 was considered statistically significant.

Results

General Information

A total of 546 patients who underwent elective total knee arthroplasty were included, along with 24 clinical characteristics and laboratory parameters (Table 1). The training set comprised 278 patients undergoing total knee arthroplasty, including 119 cases of IAPI. Compared with the non-IAPI group, the IAPI group demonstrated statistically significant differences in BMI, diabetes, frailty, edema, surgical duration, intraoperative blood loss, intraoperative hypothermia, ASA classification, and Braden score (all $p <$ 0.05). The internal validation set included 118 patients, of whom 51 developed IAPI. Significant differences between IAPI and non-IAPI groups were observed in BMI, intraoperative hypotension, intraoperative tourniquet application time, ASA classification, and Braden score (all $p <$ 0.05). The external validation set comprised 150 patients, with 60 cases of IAPI. Among them, the IAPI group exhibited statistically significant differences compared with the non-IAPI group in BMI, diabetes, surgical duration, intraoperative tourniquet application time, postoperative drain placement time, and Braden score (all $p < 0.05$).

Multifactorial Logistic Regression Analysis of IAPI in TKA Patients

Based on the results of univariate analysis, variables with $p < 0.05$ were further analyzed using multifactorial logistic regression. The results indicated that BMI and Braden score were independent risk factors for the occurrence of IAPI in TKA patients ($p < 0.05$) (Table 2). Conversely, edema, frailty, diabetes, surgical duration, ASA classification, intraoperative blood loss, and intraoperative hypothermia did not reach statistical significance ($p > 0.05$). However, their odds ratios (ORs) still suggested potential clinical relevance (e.g., surgical duration OR = 1.933). These findings may reflect limitations related to sample size or variable interactions and should be validated in larger-scale studies.

Lasso Regression Screening Characteristic Variables

The Lasso regression model was applied with IAPI diagnosis as the dependent variable and 24 potential influencing factors as independent variables. BMI and age were analyzed as continuous variables, while categorical variables were dichotomized (no = 0, yes = 1). Ultimately, eight non-zero coefficient variables were identified, including age, gender, BMI, diabetes, edema, surgical duration, Braden score, and ASA classification (Fig. 2).

Machine Learning Model Construction and Discriminative Performance Comparison

Variables identified through multivariable logistic regression and Lasso regression were incorporated into four models, LR, RF, XGBoost, and GBDT, to construct the IAPI risk prediction model. Performance was evaluated in the validation sets. In the internal validation, the GBDT model demonstrated balanced and stable performance across key indicators, including AUC, accuracy, and F1-score. Comprehensive evaluation indicated that the GBDT model provided the best discriminative performance. In the external validation, the AUC of the GBDT model (0.789) was slightly lower than that observed in the internal validation set (0.867), but remained >0.7, suggesting that the GBDT model constructed in this study has robust external generalizability (Table 3, Fig. 3).

SHAP-Based Interpretation of the Optimal Model

To enhance interpretability, SHAP values of each clinical factor were calculated for the GBDT model to quantify their contribution to the model development. Fig. 4 shows the factors that influence IAPI identification and their degree of contribution, ranked by mean absolute SHAP values. In Fig. 4B, the y-axis lists variables in order of importance (top

Table 1. Comparison of general characteristics between IAPI and non-IAPI groups in TKA patients [n (%)].

Variable	Training set				Internal validation set				External validation set			
	Non-IAPI (n = 159)	IAPI (n = 119)	$t/z/x^2$	*p*-value	Non-IAPI (n = 67)	IAPI (n = 51)	$t/z/x^2$	*p*-value	Non-IAPI (n = 90)	IAPI (n = 60)	$t/z/x^2$	*p*-value
Age, median	67 (62.00, 67.00)	68 (62.00,73.00)	–1.907	0.057	68 (65.00,71.00)	68 (63.00,73.00)	–0.444	0.657	67.87 ± 6.12	68.80 ± 6.51	–0.820	0.374
BMI (kg/m^2)	23.81 ± 2.35	26.05 ± 2.23	–8.024	<0.001	23.54 ± 2.47	26.05 ± 1.78	–6.416	<0.001	23.59 ± 2.60	25.97 ± 2.37	–5.679	<0.001
Gender			1.133	0.287			1.221	0.269			2.436	0.119
Male	55 (34.59)	34 (28.57)			21 (41.18)	21 (41.18)			32 (35.56)	29 (48.33)		
Female	104 (65.41)	85 (71.43)			46 (68.66)	30 (58.82)			58 (64.44)	31 (51.67)		
Hypertension	30 (18.87)	17 (14.29)	1.017	0.313	6 (8.96)	5 (9.80)	0.025	0.875	8 (8.89)	8 (13.33)	0.746	0.388
Diabetes	34 (21.38)	46 (38.66)	9.906	0.002	15 (22.39)	16 (31.37)	1.207	0.272	21 (23.33)	30 (50.00)	11.408	0.001
Hyperlipidemia	43 (27.04)	38 (31.93)	0.788	0.375	13 (19.40)	14 (27.45)	1.063	0.303	17 (18.89)	17 (28.33)	1.832	0.176
Coronary heart disease	14 (8.81)	18 (15.13)	2.670	0.102	6 (8.96)	5 (9.80)	0.025	0.875	10 (11.11)	5 (8.33)	0.309	0.579
Smoking	65 (40.88)	38 (31.93)	2.336	0.126	22 (32.84)	17 (33.33)	0.003	0.955	26 (28.89)	22 (36.67)	1.001	0.317
Alcohol consumption	24 (15.09)	20 (16.81)	0.150	0.699	6 (8.96)	8 (15.69)	1.255	0.263	7 (7.78)	10 (16.67)	2.831	0.092
Frailty	22 (13.84)	32 (26.89)	7.411	0.006	13 (19.40)	17 (33.33)	2.964	0.085	23 (25.56)	22 (36.67)	2.116	0.146
Edema	24 (15.09)	32 (26.89)	–2.426	0.015	8 (11.94)	10 (19.61)	1.317	0.251	11 (12.22)	11 (18.33)	–1.036	0.300
Surgical duration (>2.5 h)	38 (23.90)	42 (35.29)	4.312	0.038	18 (26.87)	20 (39.22)	2.023	0.155	18 (20.00)	22 (36.67)	5.114	0.024
Intraoperative blood loss (>200 mL)	26 (16.35)	31 (26.05)	3.927	0.048	13 (19.40)	15 (29.41)	1.603	0.206	22 (24.44)	22 (36.67)	2.594	0.107
Intraoperative hypotension	31 (19.50)	29 (24.37)	0.955	0.328	10 (14.93)	16 (31.37)	4.560	0.033	18 (20.00)	20 (33.33)	3.383	0.066
Intraoperative hypothermia	25 (15.72)	30 (25.21)	3.860	0.049	12 (17.91)	17 (33.33)	3.716	0.054	22 (24.44)	17 (28.81)	0.352	0.553
Intraoperative tourniquet application time (≥1.5 h)	57 (35.85)	49 (41.18)	0.819	0.366	14 (20.90)	20 (39.22)	4.738	0.029	24 (26.67)	26 (43.33)	4.500	0.034
Postoperative drain placement time (≥24 h)	37 (23.27)	33 (27.73)	0.719	0.397	18 (26.87)	17 (33.33)	0.581	0.446	25 (27.78)	26 (43.33)	3.882	0.049
Anesthesia method			0.517	0.472			0.451	0.502			2.920	0.088
Intravertebral	136 (85.53)	98 (82.35)			57 (85.07)	41 (80.39)			75 (83.33)	43 (71.67)		
General	23 (14.47)	21 (17.65)			10 (14.93)	10 (19.61)			15 (16.67)	17 (28.33)		
ASA classification			8.173	0.017			9.547	0.008			2.194	0.334
I	41 (25.79)	24 (20.17)			24 (35.82)	6 (11.76)			24 (26.67)	16 (26.67)		
II	57 (35.85)	29 (24.37)			21 (31.34)	18 (35.29)			31 (34.44)	27 (45.00)		
≥III	61 (38.36)	66 (55.46)			22 (32.84)	27 (52.94)			35 (38.89)	17 (28.33)		
Braden score (<18)	24 (15.09)	84 (70.59)	88.228	<0.001	9 (13.43)	31 (60.78)	28.976	<0.001	16 (17.78)	36 (60.00)	28.336	<0.001
SAS score			1.719	0.633			2.229	0.526			0.692	0.875
No anxiety	129 (81.13)	89 (74.79)			54 (80.60)	37 (72.55)			70 (77.78)	47 (78.33)		
Mild anxiety	22 (13.84)	23 (19.33)			10 (14.93)	12 (23.53)			15 (16.67)	10 (16.67)		

Table 1. Continued.

Variable	Training set				Internal validation set				External validation set			
	Non-IAPI (n = 159)	IAPI (n = 119)	$t/z/x^2$	*p*-value	Non-IAPI (n = 67)	IAPI (n = 51)	$t/z/x^2$	*p*-value	Non-IAPI (n = 90)	IAPI (n = 60)	$t/z/x^2$	*p*-value
Moderate anxiety	7 (4.40)	6 (5.04)			2 (2.99)	2 (3.92)			4 (4.44)	3 (5.00)		
Severe Anxiety	1 (0.63)	1 (0.84)			1 (1.49)	0 (0.00)			1 (1.11)	0 (0.00)		
SDS score			5.973	0.113			7.751	0.051			0.716	0.869
No depression	122 (76.73)	77 (64.71)			49 (73.13)	26 (50.98)			57 (63.33)	38 (63.33)		
Mild depression	27 (16.98)	27 (22.69)			15 (22.39)	17 (33.33)			24 (26.67)	17 (28.33)		
Moderate depression	9 (5.66)	12 (10.08)			3 (4.48)	7 (13.73)			8 (8.89)	5 (8.33)		
Severe depression	1 (0.63)	3 (2.52)			0 (0.00)	1 (1.96)			1 (1.11)	0 (0.00)		
Hypoproteinemia	21 (13.21)	25 (21.01)	2.999	0.083	13 (19.40)	17 (33.33)	2.964	0.085	12 (13.33)	14 (23.33)	2.512	0.113
Hyperlactatemia	14 (8.81)	17 (14.29)	2.063	0.151	3 (4.48)	7 (13.73)	3.193	0.074	7 (7.78)	9 (15.00)	–1.585	0.160

Note: IAPI, intraoperatively acquired pressure injury; BMI, body mass index; ASA, American Society of Anesthesiologists; SAS, self-rating anxiety scale; SDS, self-rating depression scale.

Table 2. Multivariate logistic regression analysis of risk factors for IAPI in TKA patients.

Variable	B	SE	*z*	Wald χ^2	*p*-value	OR (95% CI)
BMI	0.360	0.077	4.676	21.861	<0.001	1.434 (1.233–1.667)
Edema	0.730	0.389	1.876	3.520	0.061	2.075 (0.968–4.447)
Frailty	0.382	0.451	0.846	0.716	0.397	1.465 (0.605–3.544)
Diabetes	0.493	0.367	1.345	1.809	0.179	1.637 (0.798–3.359)
Surgical duration (>2.5 h)	0.659	0.544	1.212	1.468	0.226	1.933 (0.666–5.610)
ASA classification	0.116	0.215	0.538	0.289	0.591	1.123 (0.736–1.712)
Braden score (<18)	2.459	0.341	7.208	51.954	<0.001	11.692 (5.991–22.817)
Intraoperative blood loss	–0.524	0.641	–0.817	0.667	0.414	0.592 (0.169–2.081)
Intraoperative hypothermia	0.277	0.471	0.589	0.347	0.556	1.320 (0.524–3.321)
Intercept	–11.077	1.968	–5.629	31.683	<0.001	

OR, odds ratio.

Table 3. Discriminative performance of machine learning models for predicting IAPI in TKA patients.

Models	AUC (95% CI)	ACC	F1	SEN	SPE	PPV	NPV
Training set							
LR	0.876 (0.835–0.917)	0.812	0.772	0.739	0.868	0.807	0.816
RF	0.855 (0.809–0.901)	0.784	0.741	0.722	0.830	0.761	0.800
XGBoost	0.864 (0.822–0.906)	0.777	0.733	0.714	0.824	0.752	0.794
GBDT	0.865 (0.822–0.908)	0.788	0.747	0.731	0.830	0.763	0.805
Internal validation set							
LR	0.809 (0.731–0.886)	0.720	0.673	0.667	0.761	0.680	0.750
RF	0.820 (0.746–0.895)	0.737	0.693	0.686	0.776	0.700	0.765
XGBoost	0.860 (0.795–0.927)	0.763	0.708	0.667	0.836	0.756	0.767
GBDT	0.867 (0.799–0.934)	0.788	0.747	0.725	0.836	0.771	0.800
External validation set							
GBDT	0.789 (0.712–0.866)	0.746	0.672	0.650	0.811	0.696	0.777

Note: AUC, area under the curve; ACC, accuracy; F1, F1-score; SEN, sensitivity; SPE, specificity; PPV, positive predictive value; NPV, negative predictive value; GBDT, gradient boosting decision tree; LR, logistic regression; RF, random forest; XGBoost, extreme gradient boosting.

= highest, bottom = lowest), while the x-axis shows SHAP values, with positive values increasing the probability of IAPI identification and negative values decreasing the probability of identification. Dot color represents raw variable values (yellow = high values, purple = low values), allowing visualization of how variable levels impact predictions. The results showed that BMI, Braden score, ASA classification, age, and surgical duration were the most influential predictors of IAPI risk (Fig. 4).

Discussion

TKA is an important treatment for knee joint diseases, but IAPI is a common associated complication. This injury mainly results from the prolonged fixed position of the patient during surgery and sustained pressure on bony prominences, which leads to local tissue ischemia and hypoxia, ultimately causing skin and soft tissue injury. It is associated with factors such as advanced age, malnutrition, degenerative skin changes, and prolonged operative duration. IAPI increases patient discomfort, delays recovery, and may lead to severe complications such as infection, thereby compromising surgical outcomes and prognosis. Therefore, prevention and effective management of IAPI are essential to improving surgical success rates and quality of life of patients.

In this study, four IAPI prediction models were constructed based on machine learning algorithms: LR, RF, XGBoost, and GBDT. All models achieved high AUC values, with the GBDT model demonstrating the best integrated discriminative efficacy (AUC 0.867, sensitivity 0.725, specificity 0.836, accuracy 0.788, and F1 value 0.747), showing higher accuracy compared with similar studies. GBDT, a gradient boosting-based machine learning algorithm, iteratively fits residuals through multiple decision trees. It can effectively handle non-linear relationships, is robust against outliers, and evaluates feature importance. In clinical domains such as disease diagnosis, risk prediction, and prognosis assessment, GBDT consistently shows excellent discriminative performance. For example, in lung cancer diagnosis, positron emission tomography/computed tomography (PET/CT) imaging histology texture feature extraction technology based on the GBDT algorithm efficiently distinguished primary from metastatic lung cancer within 30 minutes, achieving an AUC value of 0.98, significantly outperforming other models and even exceeding the performance of radiologists (AUC 0.85), thereby providing strong support for early diagnosis and precision treatment for lung cancer [17]. Similarly, in predicting ciprofloxacin resistance and ESBL production in patients with urinary tract infections, the GBDT algorithm, with its built-in regularization, demonstrated excellent anti-overfitting performance in a small-sample dataset, achieving an AUC value of 0.82 and a 20% improvement in accuracy, thus providing crucial support for personalized antibiotic selection and informed precise clinical management [18]. Collectively, these applications demonstrate that GBDT yields reliable predictive outcomes when analyzing complex clinical data, thus providing robust support for clinical decision-making.

This study observed an incidence rate of IAPI of 42.8% (training set), significantly higher than that reported in previous literature (typically 5%–20%). This discrepancy primarily reflects the inclusion of Stage I injuries (pressure-induced non-blanching erythema) in the statistical analysis for early warning purposes, as well as the study population comprising high-risk TKA patients who were elderly with multiple comorbidities. This finding sensitively highlights the widespread risk of early tissue injury during surgery and provides critical evidence supporting the development of highly sensitive predictive models. In this study, the GBDT model was visualized and interpreted using the SHAP method, and the five most influential variables affecting the discriminative performance of the model were,

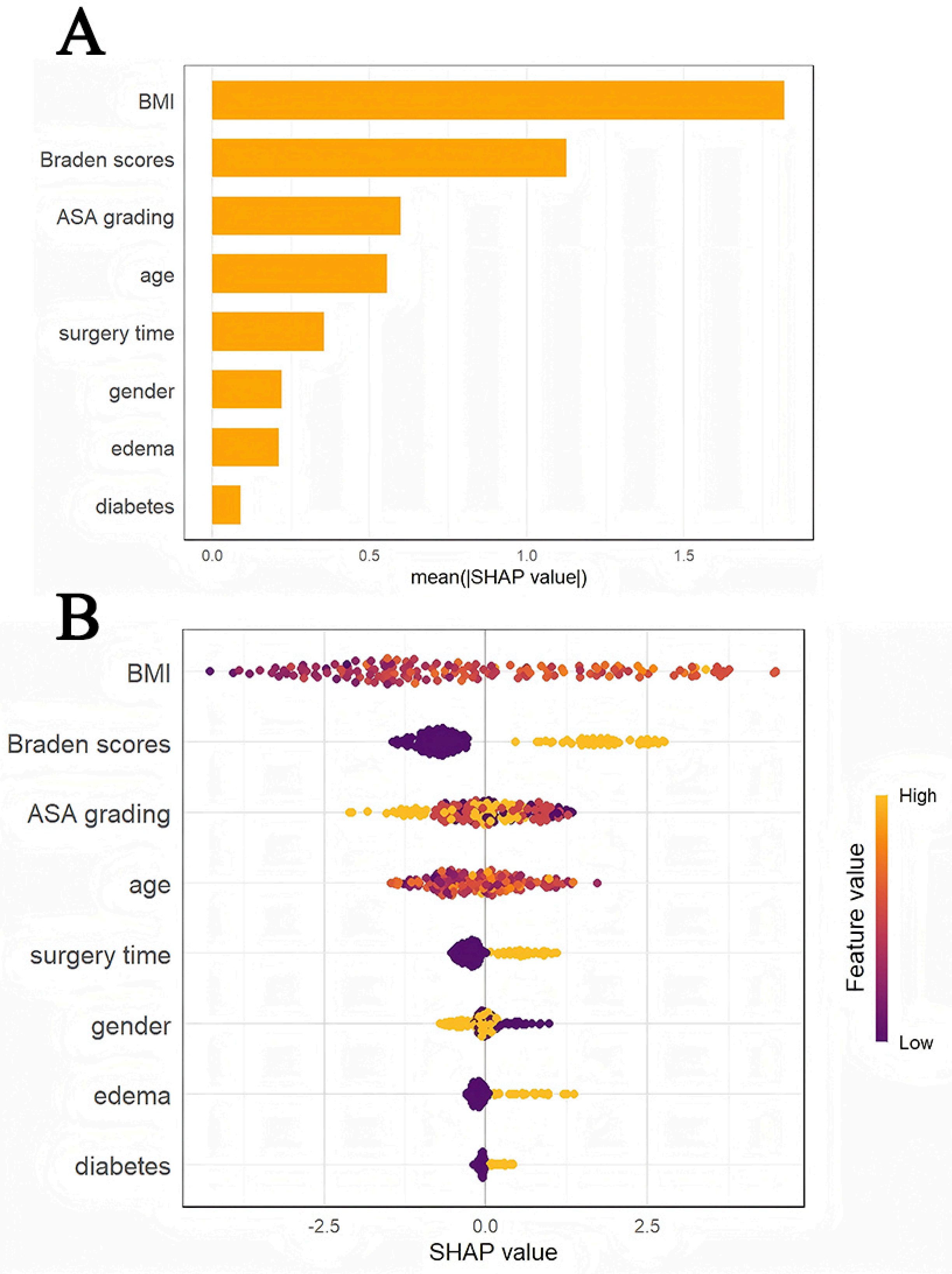

Fig. 4. Model interpretability of the optimal machine learning model. (A) Variable importance plot of predictors ranked by mean SHAP values. (B) Predictor importance ranking demonstrating the relative contribution of each variable in the final model. SHAP, Shapley additive explanation.

in order, BMI, Braden score, ASA classification, age, and surgical duration.

In total knee arthroplasty, patients are at high risk of IAPI due to intraoperative immobilization, positional constraints, and postoperative activity restriction. The Braden scale, commonly used in clinical practice for pressure injury risk assessment, effectively identifies and stratifies high-risk patients. The scale covers six dimensions: sensory perception, mobility, activity, humidity, nutrition, and friction/shear, and can identify individuals at high risk for IAPI [6]. Particularly in patients undergoing total knee arthroplasty, prolonged duration of surgery ($\geq$2 hours), fixed positioning causing localized pressure concentrations, and impaired tissue perfusion significantly increase IAPI risk. Both prolonged surgical duration and low Braden scores have been validated as independent risk factors. In clinical practice, a Braden score of $\leq$18 is generally considered the intervention threshold [19]. A preoperative score of $\leq$12 is significantly associated with the occurrence of IAPI ($p < 0.05$), while a threshold of $\leq$14.5 yields an ROC AUC of 0.735, indicating a moderate predictive efficacy. However, the Braden scale is less sensitive to intraoperative-specific risks (e.g., position-related shear) compared with specialized tools, such as the Scott Triggers Scale (AUC = 0.934). Furthermore, intraoperative factors such as hypothermia and patient repositioning may reduce the predictive power of the Braden score. Despite these limitations, the Braden Scale remains valuable for preoperative baseline risk assessment in TKA patients. For individuals with low scores ($\leq$14), reinforcing intraoperative protective measures, such as applying silicone foam dressings or implementing “micromobility” techniques (e.g., bed tilting by 15° every hour), has been shown to reduce IAPI incidence from 10% to 2% [20]. Therefore, combining the Braden Scale with intraoperative risk management and exploring multidimensional assessment tools may enhance the prevention of IAPI.

Previous studies have also confirmed a significant correlation between IAPI and age, with age $\geq$62 years identified as a major risk factor [21–23]. Elderly patients are more susceptible to tissue ischemia under intraoperative pressure due to physiological degenerative changes, including loss of dermal collagen, reduced subcutaneous fat, and impaired microcirculatory regulation, all of which weaken resistance to compression. Additionally, vasodilatation capacity is compromised by altered nitric oxide metabolism and decreased sympathetic responsiveness. Complex comorbidities and anatomical changes in elderly patients often prolong surgical time (with a sharp increase in risk beyond $\geq$4 hours) [24,25]. Moreover, supine intraoperative positioning attenuates pressure at bony prominences, while age-related thermoregulatory decline further exacerbates tissue ischemia risk. Clinical evidence indicates that the risk of IAPI increases by 1.5–2-fold for every 10-year increase in age, with patients aged $\geq$76 years exhibiting more than three-fold higher incidence compared with younger groups. This risk is particularly pronounced in underweight elderly patients with a BMI <23 kg/m^2, who are more susceptible to injury due to fragile subcutaneous tissues [26].

The relationship between BMI and IAPI exhibits complex non-linear characteristics. Studies indicate that patients with normal or low BMI (Asian standard BMI <23 kg/m^2) face a significantly higher risk of IAPI due to reduced subcutaneous fat and muscle mass, leading to insufficient pressure cushioning at bony prominences. Contrastingly, patients with overweight BMI ($\geq$23 kg/m^2) demonstrate a reduced risk, as moderate fat reserves enhance tissue resistance to compression [25,26]. However, patients with very high BMI ($\geq$28 kg/m^2) show a U-shaped risk curve due to the synergistic effects of difficult positioning, uneven pressure distribution, and increased risk of intraoperative hypothermia [27].

Body composition analyses further revealed that each 1 kg/m^2 reduction in fat-free mass was associated with a 12.7 mmHg increase in peak sacrococcygeal pressure. Among high-BMI patients with waist circumference $\geq$90 cm, iliac crest pressures could reach 98.5 mmHg, over three times the capillary closure pressure. From a metabolic perspective, hyperglycemia exacerbates microcirculatory dysfunction in diabetic patients with BMI >25 kg/m^2, counteracting the protective effect of fat buffering and thereby heightening IAPI risk [28]. Given this non-linear relationship, stratified clinical interventions are warranted. For low-BMI (BMI <18.5 kg/m^2) patients, the use of gel pads combined with intraoperative pressure monitoring is recommended, while high-BMI (BMI $\geq$28 kg/m^2) patients should undergo procedures of $\leq$2 hours in duration and maintain core body temperature >36 °C. Thus, to predict IAPI more accurately in TKA, multifactorial prediction models should incorporate body composition, metabolic indices, and intraoperative parameters rather than relying solely on BMI thresholds.

Although multivariate logistic regression only identified BMI and Braden score as independent predictors, Lasso retains other variables because penalized regression can capture nonlinear patterns and mitigate multicollinearity that traditional regression might overlook. The literature has also reported that ASA grade $\geq$ III is an independent risk factor for IAPI [29]. The mechanism is primarily attributed to impaired microcirculation and reduced tissue repair capacity caused by systemic conditions such as diabetes mellitus and cardiovascular disease, which are frequently present in higher ASA grade patients. Evidence demonstrates that the incidence of IAPI is significantly higher in ASA class III patients compared with class II patients [30], with synergistic risks observed in cases of prolonged operative time ($\geq$4 hours, 7.3-fold increased risk), hypoalbuminemia (<35 g/L), and positional adjustments (e.g., head-high-feet-low position, which increases sacrococcygeal pressures by 40%) [20]. Moreover, a study involving 325 orthopedic patients showed that patients with ASA $\geq$ grade III were more likely to sustain intraoperative injuries due to high-frequency instrument shear forces and rigid positional fixation, with risk further amplified in patients with BMI >23 kg/m^2 [21].

Given that obesity-related risks may be subjectively underestimated by ASA grading, clinical recommendations emphasize stratified prevention strategies for patients with ASA grades III–IV. These include branched-chain amino acid supplementation within 72 hours preoperatively to improve albumin levels [31] and intraoperative application of dynamic pressure monitoring systems [20]. Furthermore, it is recommended that ASA grading be optimized with objective indicators such as body fat percentage to enhance accuracy and ensure patient safety.

In total knee arthroplasty, there is a significant positive correlation between the occurrence of IAPI and operative duration. Studies have confirmed that procedures lasting $\geq$2 hours represent an independent risk factor for IAPI [32], with a 1.07-fold increase in IAPI risk for every additional hour of surgery, whereas operations exceeding 4 hours may increase the incidence of IAPI by 33% [31]. In orthopedic procedures, shear forces on bony prominences (e.g., sacrococcygeal, heel) caused by positional fixation and instrumentation significantly exacerbate tissue hypoxia, while the anesthetic state further diminishes pain feedback, rendering the pressure threshold more susceptible to breach. Prospective study has shown that the product of mean pressure and operative duration is significantly higher in IAPI cases compared with non-IAPI controls ($p < 0.01$), suggesting the critical role of cumulative pressure in surpassing tissue injury thresholds [31]. The average duration for TKA is 90–120 minutes; however, complex or revision surgeries may be prolonged beyond 4 hours, at which point the risk of IAPI rises exponentially [33,34]. In the future, individualized pressure-time thresholds should be explored, incorporating bioimpedance or body composition parameters (e.g., fat distribution) to improve the accuracy of risk assessment.

The GBDT model demonstrates the capacity to integrate electronic medical record data. For example, a 72-year-old female patient scheduled for surgery (BMI = 26.5 kg/m^2, Braden score = 13, ASA grade III, estimated surgery duration = 3 hours) underwent preoperative risk assessment. The model calculated a 78% IAPI risk probability, driven by contributions from Braden score (SHAP +0.30), BMI (+0.25), age (+0.20), estimated operative duration (+0.10), and ASA classification (+0.10). Based on this output, the system triggered a preoperative warning and recommended targeted measures, including silicone foam dressings, intraoperative temperature monitoring, and scheduled positional adjustments. When the actual surgical duration extended to 3.2 hours, the dynamic model provided real-time intervention recommendations (e.g., positional tilting). Postoperative analysis showed that the SHAP contribution value for the actual surgical duration was +0.15, raising cumulative risk probability to 82%. However, no IAPI occurred due to the implementation of measures that supported the predictive validity of the model and the effectiveness of timely intervention measures.

This study has several limitations. First, the training set was derived exclusively from Chengdu 363 Hospital Affiliated to Southwest Medical University, although external validation was performed at Chengfei Hospital; the narrow geographical distribution of patients limits its generalizability. Multicenter prospective studies are needed to enhance external validity. Second, dynamic intraoperative indicators, such as real-time pressure monitoring data during surgery, were not included. Future studies could incorporate IoT-based systems or wearable devices to improve model accuracy. Third, the number of patients with extremely high BMI ($\geq$35 kg/m^2) in the sample was limited (n = 15), necessitating larger samples to validate findings in this subgroup. Fourth, the study did not capture details of surgical positioning (e.g., use of pillows), potentially overlooking key mechanical factors. Finally, the retrospective study design inherently introduces uncontrollable confounding bias, underscoring the need for prospective validation of the findings.

Conclusions

This study compared four machine learning models, with GBDT demonstrating the highest predictive performance. SHAP analysis revealed that BMI, Braden score, ASA classification, age, and surgical duration were the top five factors influencing IAPI prediction, indicating that the integration of GBDT with SHAP can accurately identify key risk factors and support targeted clinical interventions. Future studies should include larger sample sizes and multicenter prospective studies to enhance the reliability and clinical generalizability of these findings.

Availability of Data and Materials

The data analyzed are available from the corresponding author upon reasonable request.

Author Contributions

JZ conceptualized the research study. JL and XX performed the research. XY, XC and HZ analyzed the data. JZ, JL and XC wrote the manuscript. All authors have been involved in revising it critically for important intellectual content. All authors gave final approval of the version to be published. All authors have participated sufficiently in the work to take public responsibility for appropriate portions of the content and agreed to be accountable for all aspects of the work in ensuring that questions related to its accuracy or integrity.

Ethics Approval and Consent to Participate

The research protocol was reviewed and approved by the Medical Ethics Review Committee of Chengdu 363 Hospital Affiliated to Southwest Medical University (Ethical Number: 2024-069) and adhered to the ethical standards for medical research involving human subjects as set out in the Declaration of Helsinki and its subsequent amendments. Participants provided written informed consent prior to taking part in the study.

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Conflict of Interest

The authors declare no conflict of interest.

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