

Machine learning-based prediction model for intraoperative hypothermia risk in thoracoscopic lobectomy patients

A SHAP analysis

Rui Chen, MD^a, Xiaomin Ma, MM^a, Min Liu, MD^a, Xiaosha Deng, MD^a, Fangyuan Wei, MD^a, Gui Li, MD^a, Sha Luo, MD^{a,*} 

Abstract

This study aimed to develop and evaluate a machine learning based risk prediction model for intraoperative hypothermia (IOH) in patients undergoing thoracoscopic lung cancer surgery and interpret the model using the SHapley Additive exPlanations (SHAP) method to assess the contribution of specific features to the prediction results. A retrospective analysis was conducted on 717 patients who underwent thoracoscopic lung cancer surgery at a tertiary hospital in Wuhan from January 2022 to December 2023. The dataset was randomly divided into a training set ($n = 502$) and a testing set ($n = 215$) at a 7:3 ratio. A random forest (RF) algorithm was used to build the prediction model. Model performance was assessed using accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve. The Brier score of the calibration curve was used to evaluate model fit, and decision curve analysis (DCA) was used to assess clinical utility. The SHAP method was applied to interpret the importance and influence of each predictive feature. The area under the receiver operating characteristic curve of the random forest-based prediction model in the testing set was 0.753, the F1 score was 0.80, the recall rate was 0.87, the accuracy rate was 0.732, the precision rate was 0.74, 95% CI (0.69–0.82), the sensitivity was 0.789, the specificity was 0.614, and the Brier score was 0.196. Decision curve analysis results confirmed the model's good clinical practicability. The SHAP diagram visually displayed that intraoperative infusion volume, surgery duration, age, anesthesia duration, body mass index, and hemoglobin were the 6 most important features influencing IOH risk, and there were also interaction effects between features. The SHAP method enhanced the interpretability of the machine learning model, identifying key risk factors for IOH in thoracoscopic lung cancer surgery. This approach can assist medical staff in screening high-risk factors and developing personalized hypothermia prevention programs for lung cancer patients.

Abbreviations: ASA = American Society of Anesthesiologists Physical Status Classification System, BMI = body mass index, BSA = body surface area, DCA = decision curve analysis, IOH = intraoperative hypothermia, ML = machine learning, RF = random forest, ROC = receiver operating characteristic, SHAP = SHapley Additive exPlanations.

Keywords: intraoperative hypothermia, machine learning, prediction model, random forest, SHAP, thoracoscopic surgery

1. Introduction

Intraoperative hypothermia (IOH) is defined as a core body temperature below 36°C occurring at any time during surgical procedures.^[1] A national survey conducted across 28 healthcare institutions involving 3126 patients revealed an overall IOH incidence rate of 44.5%.^[2] Extensive evidence has demonstrated that patients experiencing hypothermia exhibit multiple adverse outcomes compared to normothermic patients, including coagulation dysfunction,^[3] increased blood loss and transfusion requirements,^[4] postoperative

delirium,^[5] surgical site infections,^[6] and cardiovascular complications.^[7] Furthermore, IOH has been significantly associated with prolonged anesthesia recovery time, elevated ICU admission rates, extended hospital stays, and heightened mortality risk.^[8]

The incidence of IOH is relatively high in thoracoscopic surgery. Patients undergoing lung cancer surgery have some special pathological conditions, such as poor basic state, low body mass index (BMI), and comorbid chronic diseases like diabetes, these factors have been confirmed to be independent predictors

The authors have no funding and conflicts of interest to disclose.

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

^a Operating Room, The Central Hospital of Wuhan, Tongji Medical College, Huazhong University of Science and Technology, Wuhan, China.

* Correspondence: Sha Luo, Operating Room, The Central Hospital of Wuhan, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430014, China (e-mail: 19947697126@163.com).

Copyright © 2025 the Author(s). Published by Wolters Kluwer Health, Inc. This is an open-access article distributed under the terms of the Creative Commons Attribution-Non Commercial License 4.0 (CCBY-NC), where it is

permissible to download, share, remix, transform, and build upon the work provided it is properly cited. The work cannot be used commercially without permission from the journal.

How to cite this article: Chen R, Ma X, Liu M, Deng X, Wei F, Li G, Luo S. Machine learning-based prediction model for intraoperative hypothermia risk in thoracoscopic lobectomy patients: A SHAP analysis. *Medicine* 2025;104:35(e44202).

Received: 15 May 2025 / Received in final form: 25 June 2025 / Accepted: 10 August 2025

<http://dx.doi.org/10.1097/MD.00000000000044202>

of IOH.^[9] In addition, thoracoscopic lobectomy also has unique risk factors that contribute to the high incidence of IOH. These include the high surgical risk level, exposure of the body cavity in the laminar flow environment of the operating room, and a large volume of intraoperative irrigation, all of which further increase the risk of body temperature imbalance in patients.^[10] According to relevant data, the incidence of hypothermia can be as high as 78.3% in patients undergoing thoracoscopic surgery.^[4] Specifically, the incidence of IOH in patients undergoing thoracoscopic surgery is approximately 53.2%.^[11] Moreover, 41.89% of patients still had hypothermia when entering the postanesthesia care unit after surgery.^[12]

The risk factors of hypothermia in patients undergoing thoracoscopic lung cancer surgery include: demographic characteristics^[13]; including age, BMI, body surface area (BSA), combined diabetes, preoperative body temperature, etc; laboratory indicators^[14]; including hemoglobin, white blood cells, platelet, total bilirubin, combined hypertension, etc; operation-related parameters^[15]; including surgery duration, intraoperative blood loss, intraoperative infusion volume, American Society of Anesthesiologists Physical Status Classification System, etc.

IOH is associated with numerous risk factors. Accurate prediction and early intervention are the most effective measures to prevent IOH. In terms of model construction, researchers have widely used multivariate regression analysis, machine learning (ML), and other techniques, combined with clinical data and electronic medical record information, to develop prediction tools that are both highly accurate and operationally feasible. Studies have proved that ML methods have shown significant advantages in medical big data statistics, which can quickly and effectively process complex big data and improve the accuracy and efficiency of models.^[16,17] However, in terms of clinical disease prognosis, many ML risk prediction models still have limitations in application and interpretability.^[18] In this study, based on the retrospective clinical data of patients undergoing thoracoscopic lung cancer surgery, the random forest (RF) algorithm of ML was used to develop a prediction tool, and the

prediction effect of the model was verified. At the same time, SHapley Additive exPlanations (SHAP) value was applied to the human-machine collaboration framework to provide intuitive interpretation of the prediction results. This approach allows clinical staff to identify early and more accurately factors associated with hypothermia, thus providing important insights into reducing the incidence of IOH in patients undergoing thoracoscopic lung cancer surgery.

2. Methods

2.1. Study design

This study employed a retrospective design, involving a cohort of 813 patients diagnosed with lung cancer who underwent lobectomy at a tertiary hospital in Wuhan between January 2022 and December 2023. Inclusion criteria: age ≥ 18 years; patients diagnosed with lung cancer and undergoing lobectomy; elective surgery conducted via thoracoscopic surgery^[19]; receipt of general anesthesia; signed the informed consent for tumor resection; and complete medical data. Exclusion criteria: impairment of the thermoregulatory center; unable to monitor nasopharyngeal temperature due to nasal surgery or abnormalities; and occurrence of massive hemorrhage, shock, or respiratory and cardiac arrest during the operation. Figure 1 shows the flowchart of this study.

2.2. Sample

Drawing upon a comprehensive review of the literature and insights from expert practitioners, this study identified and screened potential predictors, ultimately incorporating 27 risk factors into the analysis. To achieve reliable parameter estimation, it is recommended that the sample size be 10 to 15 times the number of independent variables.^[20] Accordingly, the required sample size for this study was calculated to range from 338 to 507 participants. From the database, 813 cases were initially

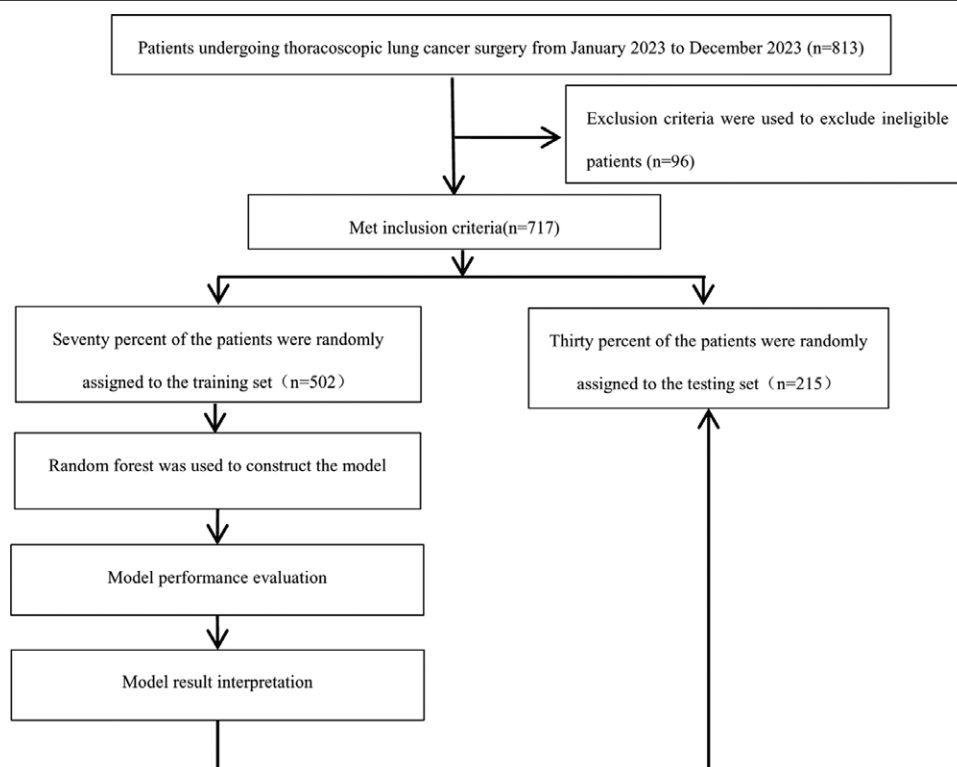


Figure 1. Patient selection and technology roadmap.

extracted, with 96 cases excluded for not meeting the inclusion criteria. To ensure data accuracy, all eligible cases were retained, resulting in a final sample size of 717 cases. This dataset was then randomly divided into a training set comprising 502 cases (70%) and a testing set consisting of 215 cases (30%).

2.3. Ethical consideration

This study was conducted in accordance with the TRIPOD guidelines and Declaration of Helsinki. It received approval from the Ethics Committee of Wuhan Central Hospital (approval number: WHZXKYL2024-011-01). This study was exempted from the requirement for obtaining informed consent.

2.4. Measurements of hypothermia

The core body temperature of patients was monitored using the zero heat-flux (deep forehead) method recommended by the National Institute for Health and Care Excellence.^[21] The temperature sensing probe embedded in the anesthesia monitor was inserted into the upper 1/3 depth of the nasopharynx, about 10 cm, and the core body temperature was monitored in real time.^[9] The nasopharyngeal temperature of the patients was recorded every 5 minutes from the completion of anesthesia induction until the end of the operation, and the changes in body temperature were dynamically monitored. In order to reduce the influence of the environment on the patient's body temperature, the temperature in the operating room was kept constant between 22°C and 24°C. If the patient's body temperature was lower than 36°C at any time point during the operation, it was considered as IOH.

2.5. Predictive factors

All retrospective data for this study were sourced from the hospital information system. A self-administered information collection form was developed to gather general patient information. The dataset comprised 27 clinical, demographic, and laboratory indicators, which were utilized for both the training and testing sets. General indicators included age, BMI, BSA, combined hypertension, combined diabetes, chronic obstructive pulmonary disease, smoking history, drinking history, and operation history, as well as preoperative body temperature. Biochemical indicators encompassed red blood cells, white blood cells, platelet, hemoglobin, D-dimer, creatinine, uric acid, albumin, total bilirubin, prothrombin time, and activated partial thromboplastin time. Intraoperative monitoring indicators included the surgery duration, inhaled desflurane, American Society of Anesthesiologists Physical Status Classification System, anesthesia duration, intraoperative blood loss, and intraoperative infusion volume. All study data were entered and verified by 2 individuals, with missing values addressed through listwise deletion and mean imputation.

2.6. Statistical analysis

The data were analyzed using SPSS version 26.0 (IBM, Armonk) to evaluate the baseline characteristics of the training and testing groups. Continuous variables were expressed as mean $\pm$ standard deviation. For those that conform to a normal distribution, the *t*-test was used. Continuous variables with a skewed distribution were represented by [M(P25, P75)], and the Mann-Whitney *U* test was applied. Categorical variables were expressed as frequency and percentage (n, %), with between-group comparisons performed using the chi-square test (χ^2). All statistical analyses were conducted using two-sided tests, with a significance level established at $P < .05$.

Python version 3.13 (Global open-source community) was used to construct the risk prediction model. RF algorithm was

used for data analysis (version 3.13 and the following packages: “pandas,” “math,” “numpy,” “matplotlib,” and “SHAP”). Bootstrap method was used for internal validation of the model with 1000 replicates. The receiver operating characteristic (ROC) curve was used to evaluate the discrimination of the model, the calibration curve was used to evaluate the fit of the model, the decision curve analysis (DCA) was used to evaluate the clinical utility, and the SHAP method was used to explain the results of the prediction model.

3. Results

3.1. Sample characteristics

A total of 717 patients were randomly divided into a training set (502 patients) and a testing set (215 patients) for internal validation. The mean age of patients undergoing thoracoscopic lung cancer surgery was 60 years, with an IOH incidence of 61.09%. Among the parameters related to the results, there was no significant difference in age, hemoglobin, BMI, and anesthesia duration between the 2 groups, except for intraoperative infusion volume and surgery duration. This indicates that the training set and testing set were similar and comparable in overall characteristics. Table 1 lists a detailed comparison of clinical characteristics between the training and testing sets.

3.2. Model performance evaluation

The bootstrap method was used to verify the RF model with 1000 replicates. ROC curve was assessed to evaluate the model's discriminatory ability. The model demonstrated an accuracy of 0.732, a precision of 0.74, a recall of 0.87, and an F1 score of 0.80. The area under the ROC curve was 0.753, 95% CI (0.69–0.82). The sensitivity and specificity were 0.789 and 0.614. This result suggested that the model exhibited good discrimination, as illustrated in Figure 2. Calibration was employed to assess the model's fit, yielding a Brier score of 0.196. This score indicates that the model's calibration performance is satisfactory and accurately reflects the actual probability of occurrence, the calibration curve is shown in Figure 3. The DCA revealed a threshold probability range between 0.05 and 0.95, with a net benefit rate exceeding 0, signifying that the model possesses substantial clinical applicability. Figure 4 shows the DCA. Model performance is summarized in Table 2.

3.3. Model result interpretation

In this study, we introduced the SHAP model to build an interpretability framework for the ML based prediction model. The SHAP values were used to evaluate each predictive feature's contribution to hypothermia occurrence, providing an intuitive explanation of the model's predictions. SHAP, proposed by Lundberg,^[22] accurately calculates the SHAP value for each feature, clearly revealing their importance and evaluating the contribution of all feature combinations to the model's overall predictive ability. This provides consistent and accurate attribution analysis for each feature. Additionally, the SHAP summary graph aggregates multiple features to present a global perspective, enabling researchers to visualize the importance of different variable features through the SHAP values of each feature sample in the dataset.^[23,24]

In this study, Figure 5 shows the 20 variables ranked by SHAP value in the RF model, with feature importance decreasing in descending order. The top 6 variables were intraoperative infusion volume, surgery duration, age, anesthesia duration, BMI, and hemoglobin. Figure 6 illustrates the impact of these top 6 variables on the RF model predictions, considering the strongest interactions. For example, Figure 6A shows that age interacts most frequently with

Table 1
Characteristics of the included patients.

Variable	Total (n = 717)	Training set (n = 502)	Testing set (n = 215)	Statistic	P value
Age (yr, Mean ± SD)	60.78 ± 10.71	60.88 ± 10.93	60.52 ± 10.21	$t = 0.415$	.678
Hemoglobin (g/L, Mean ± SD)	133.10 ± 15.93	133.15 ± 15.62	132.97 ± 16.67	$t = 0.136$	.891
Red blood cells ($10^{12}/L$, Mean ± SD)	4.33 ± 0.50	4.34 ± 0.50	4.32 ± 0.51	$t = 0.560$	.576
BMI [n (%)]				$\chi^2 = 0.514$	.773
<18.5 kg/m ²	72 (10.04)	49 (9.76)	23 (10.70)		
18.5–23.9 kg/m ²	351 (48.95)	243 (48.41)	108 (50.23)		
>23.9 kg/m ²	294 (41.01)	210 (41.83)	84 (39.07)		
Smoking history [n (%)]				$\chi^2 = 0.115$	.735
Yes	203 (28.31)	144 (28.69)	59 (27.44)		
No	514 (71.69)	358 (71.31)	156 (72.56)		
Drinking history [n (%)]				$\chi^2 = 0.784$	.376
Yes	85 (11.85)	56 (11.16)	29 (13.49)		
No	632 (88.15)	446 (88.84)	186 (86.51)		
COPD history [n (%)]				$\chi^2 = 0.891$	.345
Yes	35 (4.88)	27 (5.38)	8 (3.72)		
No	682 (95.12)	475 (94.62)	207 (96.28)		
Combined hypertension [n(%)]				$\chi^2 = 0.235$	.628
Yes	263 (36.68)	187 (37.25)	76 (35.35)		
No	454 (63.32)	315 (62.75)	139 (64.65)		
Combined diabetes [n (%)]				$\chi^2 = 0.960$	.327
Yes	109 (15.20)	72 (14.34)	37 (17.21)		
No	608 (84.80)	430 (85.66)	178 (82.79)		
Operation history [n (%)]				$\chi^2 = 0.354$	.552
Yes	369 (51.46)	262 (52.19)	107 (49.77)		
No	348 (48.54)	240 (47.81)	108 (50.23)		
ASA [n (%)]				$\chi^2 = 13.584$	.001*
I	23 (3.21)	20 (3.98)	3 (1.40)		
II	471 (65.69)	309 (61.55)	162 (75.35)		
III	223 (31.10)	173 (34.47)	50 (23.25)		
Inhaled desflurane [n (%)]				$\chi^2 = 4.973$	.026*
Yes	541 (75.45)	367 (73.11)	174 (80.93)		
No	176 (24.55)	135 (26.89)	41 (19.07)		
Surgery duration [n (%)]				$\chi^2 = 28.120$	<.001*
>3 h	241 (33.61)	138 (27.49)	103 (47.91)		
≤3 h	476 (66.39)	364 (72.51)	112 (52.09)		
Anesthesia duration [n(%)]				$\chi^2 = 3.079$	.079
>180 min	575 (80.20)	394 (78.49)	181 (84.19)		
≤180 min	142 (19.80)	108 (21.51)	34 (15.81)		
Intraoperative infusion volume [n (%)]				$\chi^2 = 28.800$	<.001*
>1500 mL	252 (35.15)	145 (28.88)	107 (49.77)		
≤1500 mL	465 (64.85)	357 (71.12)	108 (50.23)		
Intraoperative blood loss [n(%)]				$\chi^2 = 11.321$	.001*
>100mL	139 (19.39)	81 (16.14)	58 (26.98)		
≤100mL	578 (80.61)	421 (83.86)	157 (73.02)		
BSA [m ² , M(Q1,Q3)]	1.58 (1.36–1.73)	1.56 (0.89–1.72)	1.60 (1.46–1.74)	$Z = -2.586$	.010*
Preoperative body temperature [°C, M(Q1,Q3)]	36.50 (36.40–36.60)	36.50 (36.40–36.60)	36.50 (36.40–36.60)	$Z = -1.619$	.105
White blood cells [$10^9/L$, M(Q1, Q3)]	5.75 (4.71–6.97)	5.68 (4.67–7.09)	5.87 (4.86–6.89)	$Z = -0.598$	.550
Platelet [$10^9/L$, M(Q1,Q3)]	211 (178.50–253.00)	211 (179.75–252.00)	209 (178.00–255.00)	$Z = -0.260$	.795
Albumin [g/L, M(Q1,Q3)]	42.40 (39.20–45.00)	42.40 (39.28–45.03)	42.50 (38.80–45.00)	$Z = 0.070$	.944
TBIL [μmol/L, M(Q1,Q3)]	12.90 (9.40–16.50)	12.65 (9.28–16.40)	13.20 (9.80–16.90)	$Z = -0.955$	.340
D-Dimer [μg/mL, M(Q1,Q3)]	0.36 (0.18–0.51)	0.36 (0.19–0.56)	0.35 (0.18–0.51)	$Z = -0.881$	.378
Uric acid [μmol/L, M(Q1,Q3)]	333 (262.00–398.00)	323 (251.00–388.25)	345 (284.00–409.00)	$Z = -2.920$	.004*
Creatinine [μmol/L, M(Q1,Q3)]	66.90 (55.15–75.35)	66.40 (54.98–75.50)	67.90 (56.00–74.20)	$Z = -0.007$	.994
Prothrombin time [s, M(Q1,Q3)]	11.10 (10.50–11.90)	11.20 (10.60–12.10)	11.00 (10.50–11.70)	$Z = -1.491$	.136
Activated partial thromboplastin time [s, M(Q1,Q3)]	26.60 (23.95–29.75)	26.60 (23.98–30.10)	26.70 (23.90–29.50)	$Z = -0.716$	.474

BSA = $0.0061 \times \text{height (cm)} + 0.0124 \times \text{weight (kg)} - 0.0099$.

BMI = body mass index, BSA = body surface area, COPD = chronic obstructive pulmonary disease, TBIL = total bilirubin.

*P-value <0.05 was considered statistically significant.

BMI, and there is a positive correlation between age and predicted outcomes. When age exceeds 60 years, the SHAP value increases exponentially, indicating a sharp rise in the risk of IOH in elderly patients. The color gradient in the figure reveals that individuals with high BMI and age <60 generally have lower SHAP values, suggesting a lower risk of hypothermia. Figure 6C highlights that BMI significantly

affects the prediction of IOH, with hypertension complicating and enhancing this effect, especially at higher BMI values. Figure 6D shows that hemoglobin level significantly impacts the predicted outcome of IOH, depending on the actual hemoglobin value and anesthesia duration. Longer anesthesia duration have a more pronounced effect on hemoglobin, suggesting its importance in predicting IOH during prolonged

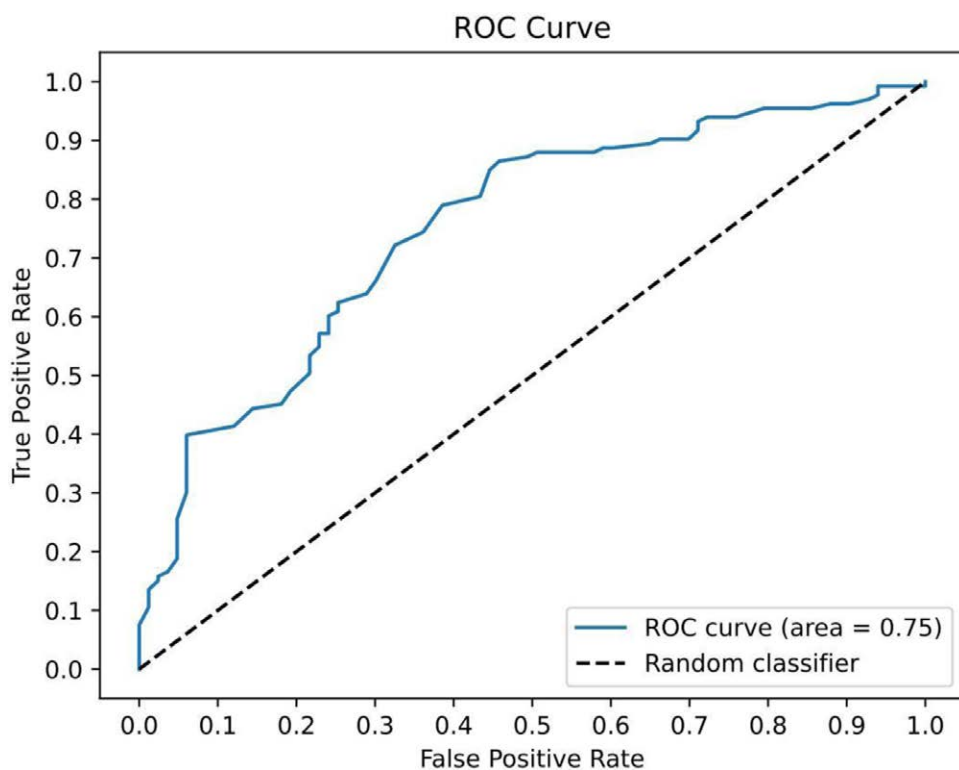


Figure 2. ROC curves of the prediction model. ROC = receiver operating characteristic.

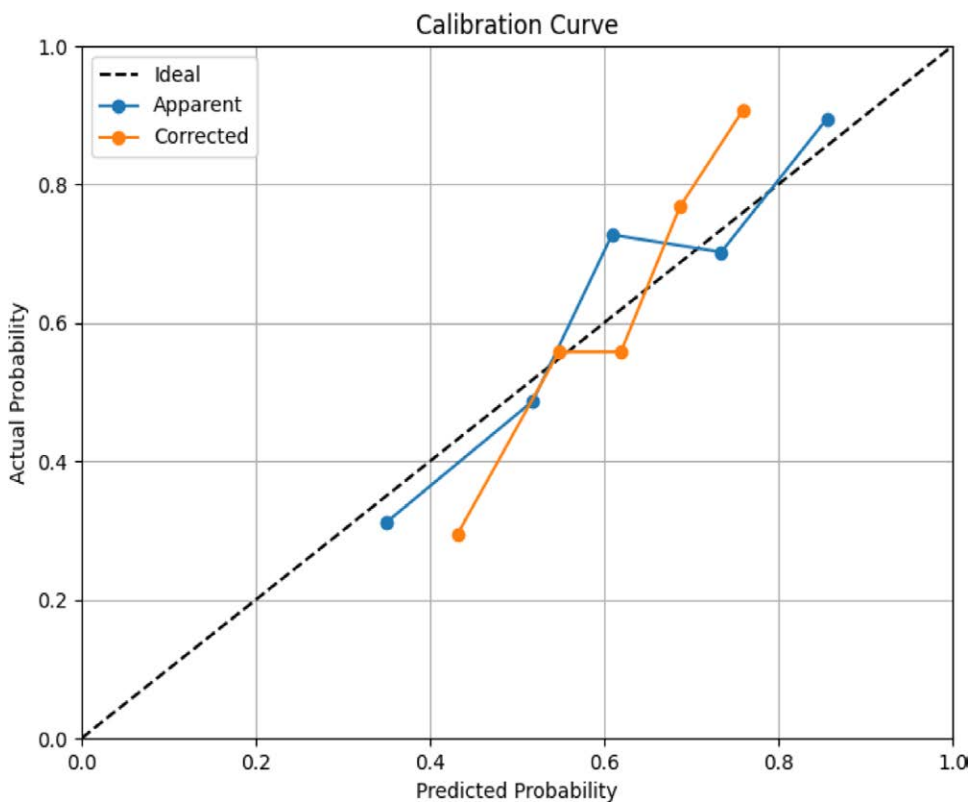


Figure 3. Calibration curve of the prediction model.

anesthesia. Additionally, other interactions with clinical relevance were observed, such as between operation duration and BSA, infusion volume and inhaled gas, and anesthesia duration and smoking history.

4. Discussion

IOH is a common perioperative complication. Early international studies showed that the incidence of hypothermia after induction of anesthesia was between 50% and 90%,^[25] while

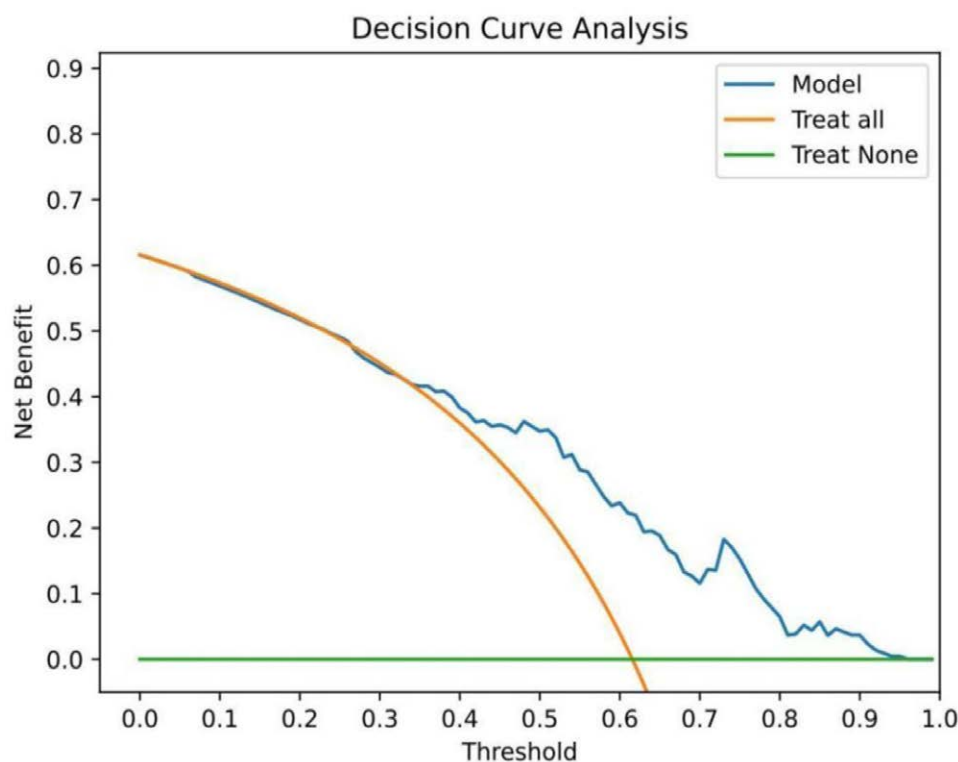


Figure 4. Decision curve analysis of the prediction model.

Table 2

Random forest model performance importance values.

Model	Accuracy	Precision	Recall	F1	ROC	Sensitivity	Specificity	Brier score
RF	0.732	0.74	0.87	0.80	0.753	0.789	0.614	0.196

RF = random forest, ROC = receiver operating characteristic.

epidemiological investigation in China revealed that hypothermia after induction of anesthesia showed a progressive cumulative feature^[8]; the incidence was 17.8%, 36.2%, 42.5%, and 44.1% within 1 to 4 hours after surgery, respectively. Focusing on the field of tumor surgery, multi-center studies have shown that the incidence of hypothermia in 200 patients is 42%,^[26] especially in lung cancer surgery, the incidence is as high as 53.2%.^[11] In a study predicting the risk of hypothermia in patients undergoing lobectomy, the rate of IOH was found to be 65.28%,^[4] which is similar to the 61.09% observed in our study and notably higher than that observed in general surgical procedures. Based on this clinical feature, this study aims to construct an interpretable ML collaborative model to realize individualized early warning of the risk of IOH in lung cancer patients through feature engineering optimization and SHAP value analysis, so as to provide decision support for precise temperature management.

As an important branch of artificial intelligence, ML has demonstrated significant application value in the medical field by integrating methods from statistics and computer science. Its core advantage lies in mining nonlinear relationships from complex data and assisting clinical decision-making.^[27] In this study, we constructed a risk prediction model for IOH based on the RF algorithm. Compared with traditional logistic regression, the RF algorithm not only automatically captures the interactions between variables but also provides accurate targets for clinical intervention through the ranking of feature importance. Based on

multi-dimensional data from perioperative patients undergoing lung cancer surgery (including demographic characteristics, laboratory indicators, and operation-related factors), the model validation showed an area under the ROC curve of 75.30% and an accuracy of 0.732. Other indicators of the model's predictive ability, such as sensitivity, specificity, F1 score, and Brier score, were also calculated, confirming its reliable predictive efficacy. This result highlights the technical advantages of ML in dynamic risk stratification. The model not only enhances the transparency of clinical decision-making through interpretable feature analysis but also provides a quantitative basis for formulating preoperative preventive warming strategies. It should be emphasized that such prediction tools and algorithm programs can be embedded in monitoring equipment to assist medical staff in optimizing individualized hypothermia prevention programs. However, the final clinical decision should still be comprehensively studied and evaluated in combination with professional experience.^[28,29]

In this study, we applied the SHAP framework to the RF model. With the help of SHAP analysis chart, we analyzed the key factors affecting IOH in patients undergoing thoracoscopic lung cancer surgery. The results showed that intraoperative infusion volume, surgery duration, age, anesthesia duration, BMI, and hemoglobin were the 6 most important variables affecting IOH in patients.

In terms of surgical factors, intraoperative infusion volume, surgery duration, and anesthesia duration were the main factors

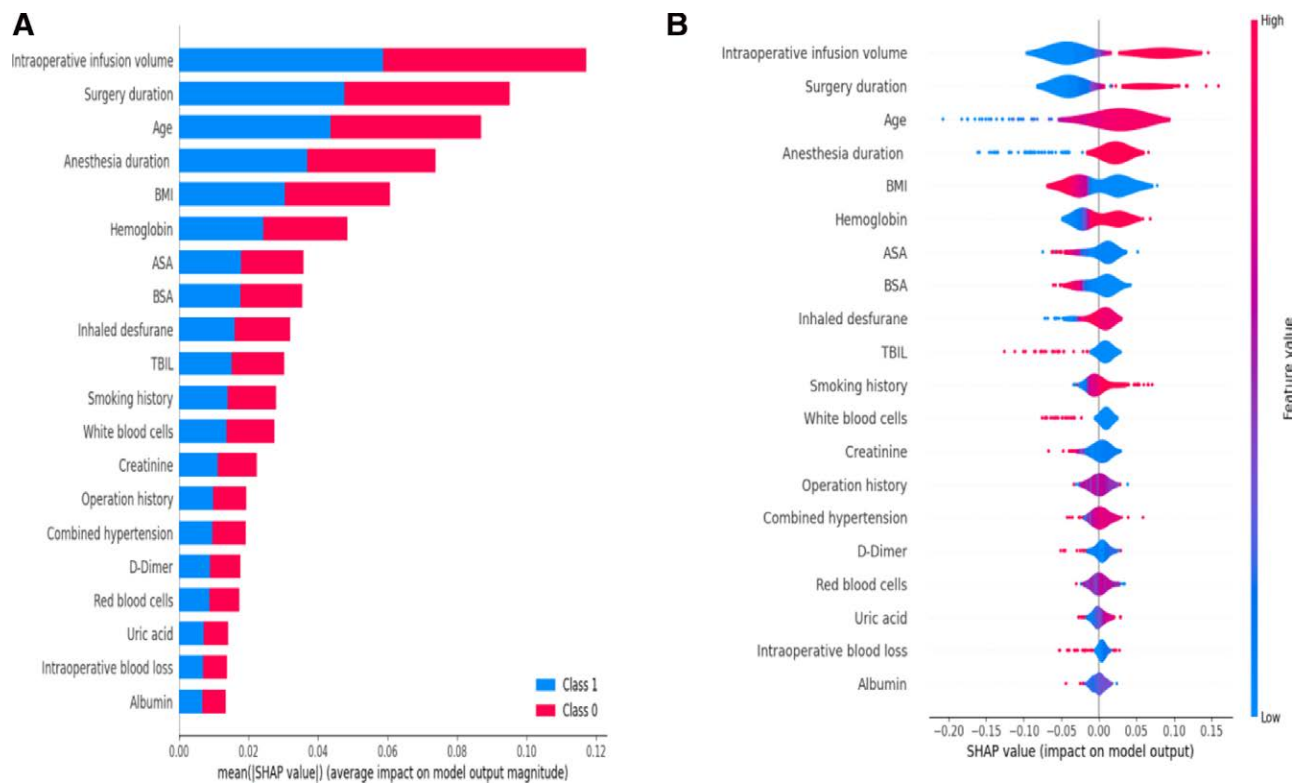


Figure 5. SHAP interpretation of the RF model constructed by machine learning. (A) Ranking of importance of features predicted by the model. The abscissa represents the SHAP value, the higher SHAP value indicates the more important the variable, Class 1 represents the contribution of the feature to the occurrence of intraoperative hypothermia, and Class 1 represents the contribution of the feature to the absence of intraoperative hypothermia. The length of the bar graph indicates the influence of the feature on the output of the model. The longer the length, the greater the influence. (B) Each point represents a feature value, and different colors represent the final influence of the feature on the output result of the model, where red represents the larger value and blue represents the smaller value. BMI = body mass index, BSA = body surface area, RF = random forest, SHAP = SHapley Additive exPlanations, TBIL = total bilirubin.

affecting body temperature change. Our study showed a strong association between the infusion of more than 1500 mL of unheated fluid and the incidence of IOH, which is consistent with the results of previous studies.^[30] Intravenous administration of 1000 mL of fluid has been reported to lower core body temperature by 0.25°C,^[31] whereas 418 kJ of heat needs to be absorbed per kilogram of fluid to raise body temperature by 1°C.^[32] Therefore, it is recommended that fluids infused to surgical patients be actively warmed to 36°C to 37°C during surgery to reduce the risk of IOH.^[33,34]

Surgery duration and anesthesia duration are common factors affecting IOH. Our study showed that the duration of surgery and anesthesia longer than 180 minutes under general anesthesia were associated with an increased risk of IOH, a finding that is consistent with findings in the existing literature.^[4] Related studies confirmed that 60 minutes after the operation, the patient's body temperature gradually dropped to about 36.1°C. The body temperature could be stabilized at about 36.0°C during 60 to 120 minutes of operation. However, between 120 and 180 minutes during surgery, the rate of hypothermia increases significantly, often to below 36.0°C, significantly increasing the risk of IOH.^[35] In thoracoscopic surgery, the large incision area exposes the body surface to low temperature, which accelerates heat loss. At the same time, the duration of anesthesia increases with the duration of surgery, and the inhibition of central thermoregulation and peripheral vasodilatation by anesthetics deepens.^[36] All general anesthetics are known to substantially impair normal autonomic thermoregulatory control, directly leading to the development of hypothermia.^[34] Therefore, compared with other surgeries, thoracoscopic lung cancer surgery requires special attention to the cumulative impact of operation and anesthesia duration on body temperature. Proactive body

temperature monitoring and preventive measures should be implemented.

In terms of individual factors, this study found that age and BMI were independent and interacting factors affecting IOH. Age-adjusted effect of BMI^[9]: in the elderly group, lower BMI was associated with a higher risk of hypothermia; However, in the younger age group, the independent effect of BMI was more significant, and the moderating effect of age was weaker. Previous studies have shown that patients with a BMI > 23.9 kg/m² have a protective effect against hypothermia, and when the body temperature decreases, patients with more body fat are more likely to stimulate vasoconstriction to reduce heat conduction to peripheral tissues and thereby contribute to the maintenance of body temperature homeostasis.^[35] Patients with BMI < 18.5 kg/m² have less muscle and adipose tissue, resulting in relatively reduced heat production and poor warming effect on core temperature, which is a risk factor for IOH.^[4] Therefore, in clinical practice, it is essential to implement preventive measures such as active and passive warming in advance to minimize the risk of IOH in elderly surgical patients with low BMI.

In terms of laboratory indicators, this study showed that hemoglobin plays an important role in predicting IOH. Previous studies have mainly focused on the relationship between postoperative anemia and recovery, potentially underestimating the importance of anemia in intraoperative temperature management.^[4] In this study, the ML model revealed the independent effect of hemoglobin on intraoperative temperature, providing a new theoretical basis for managing IOH. The potential mechanisms underlying the effect of hemoglobin on body temperature are as follows^[37]: patients with low hemoglobin have reduced oxygen-carrying capacity, which may lead to decreased metabolic heat production due

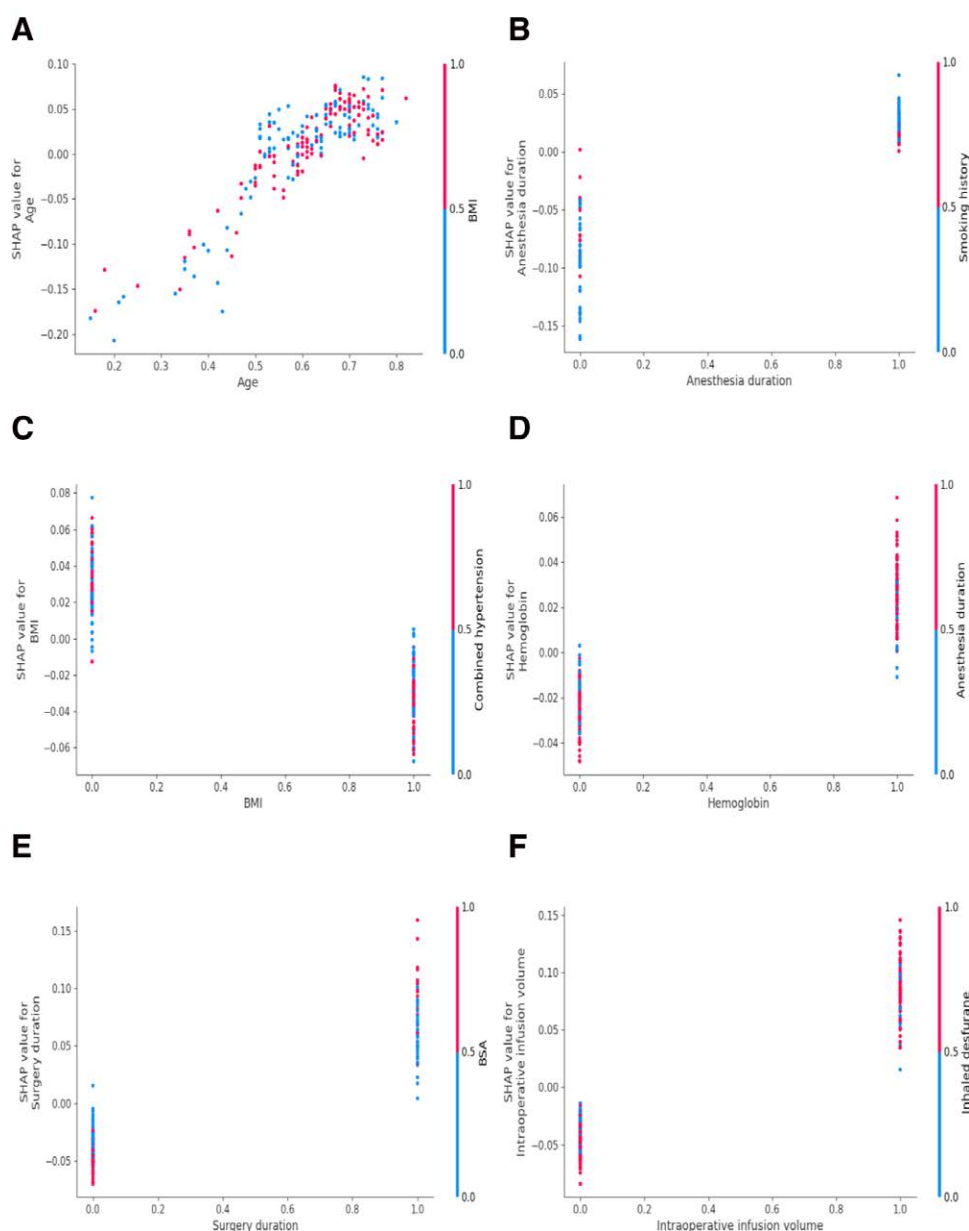


Figure 6. (A–F) are the SHAP-related graphs of the key variables. The impact of the first 6 variables and the variables most relevant to their respective interactions on SHAP values, with each point representing a single patient in the dataset. SHAP = SHapley Additive exPlanations.

to insufficient oxygen supply to tissues. Additionally, anemia may reflect poor preoperative nutritional status and impair the body's compensatory ability for temperature regulation. These findings highlight the need for clinical staff to pay closer attention to patients' hemoglobin levels during preoperative evaluations. Instead of focusing solely on postoperative outcomes, laboratory monitoring should also aim to identify preoperative risk factors, thereby enhancing intraoperative temperature management.

4.1. Study limitations

There are several major limitations of this study. Firstly, the data source is confined to a single-center retrospective study conducted in specific regions of China, lacking an external validation cohort. We propose that further external validation using large-scale sample data is essential to enhance the model's generalizability. Secondly, regarding model

interpretability, although the SHAP algorithm effectively elucidates the quantitative relationship between characteristic variables and prediction outcomes, it is important to note that this game theory-based interpretation method essentially falls within the domain of correlation analysis. Causal inference for medical decisions must be interpreted in conjunction with clinicopathological mechanisms and biological principles. Lastly, concerning modeling methodologies, more advanced deep learning techniques for constructing medical risk models could yield superior predictive outcomes. In the future, ML has the potential to evolve into deep learning in the field of preventing IOH. By conducting in-depth analysis of patients' medical records, lifestyle factors, and relevant medical images, deep learning models can be seamlessly integrated with clinical decision support systems. This integration will enable the models to more accurately predict the risk of hypothermia in advance and tailor personalized preventive measures for each patient.

5. Conclusion

In this study, we constructed a prediction model based on the RF method, which was internally validated to have good discrimination and clinical utility in identifying the risk of IOH in patients undergoing thoroscopic lung cancer surgery. In addition, the use of advanced SHAP technology for model interpretation and visualization can accurately explore the risk factors of hypothermia in patients, which can provide a reference for medical staff to screen the high-risk factors of IOH in patients with lung cancer and formulate personalized prevention plans for hypothermia.

Author contributions

Conceptualization: Rui Chen, Xiaomin Ma, Gui Li, Sha Luo.

Data curation: Min Liu, Xiaosha Deng, Fangyuan Wei, Gui Li.

Formal analysis: Xiaomin Ma.

Investigation: Gui Li.

Methodology: Rui Chen.

Supervision: Sha Luo.

Validation: Sha Luo.

Writing – original draft: Rui Chen.

Writing – review & editing: Rui Chen, Xiaomin Ma, Sha Luo.

References

- [1] National Center for Quality Assurance of Anesthesia. 2023 Chinese expert consensus statement for prevention and management of perioperative hypothermia (Chinese). *Med JPUMCH*. 2023;14:764–71.
- [2] Xu H, Wang Z, Guan X, et al. Safety of intraoperative hypothermia for patients: meta-analyses of randomized controlled trials and observational studies. *BMC Anesthesiol*. 2020;20:202.
- [3] Mendona FT, Ferreira JDS, Guillard VHF, et al. Prevalence of inadvertent perioperative hypothermia and associated factors: a cross-sectional study. *Ther Hypothermia Temp Manag*. 2021;11:208–15.
- [4] Xia F, Li Q, Xu L, et al. Development and validation of an intraoperative hypothermia nomograph model for patients undergoing video-assisted thoracoscopic lobectomy: a retrospective study. *Sci Rep*. 2024;14:15202.
- [5] Zarour S, Weiss Y, Abu-Ghanim M, et al. Association between intraoperative hypotension and postoperative delirium: a retrospective cohort analysis. *Anesthesiology*. 2024;141:707–18.
- [6] Zheng XQ, Huang JF, Lin JL, Chen D, Wu A-M. Effects of preoperative warming on the occurrence of surgical site infection: a systematic review and meta-analysis. *Int J Surg*. 2020;77:40–7.
- [7] Frank SM, Fleisher LA, Breslow MJ, et al. Perioperative maintenance of normothermia reduces the incidence of morbid cardiac events. A randomized clinical trial. *JAMA*. 1997;277:1127–34.
- [8] Yi J, Lei Y, Xu S, et al. Intraoperative hypothermia and its clinical outcomes in patients undergoing general anesthesia: National study in China. *PLoS One*. 2017;12:e0177221.
- [9] Ma XM, Fu AD, Chen R, et al. Research progress of intraoperative hypothermia management in patients with severe trauma (Chinese). *Nurs Res*. 2024;38:662–6.
- [10] Zhang B, Pan AF. Development and evaluation of a novel predictive nomogram for assessing the risk of intraoperative hypothermia in patients undergoing thoracoscopic pulmonary tumor surgery. *Heliyon*. 2023;9:e22574.
- [11] Gu XP, Yi J, Pei LJ. Expert consensus on prevention and treatment of perioperative hypothermia (2023 edition, Chinese). *J Clin Anesthesiol*. 2023;39:764–71.
- [12] Chen G, Liu QL, Xu WQ, et al. Status of hypothermia in the recovery room among patients undergoing thoracoscopic lobectomy and its influencing factors (Chinese). *Chin J Nurs*. 2022;37:42–5.
- [13] Li Y, Liang H, Feng Y. Prevalence and multivariable factors associated with inadvertent intraoperative hypothermia in video-assisted thoracoscopic surgery: a single-center retrospective study. *BMC Anesthesiol*. 2020;20:25.
- [14] Dai Z, Zhang Y, Yi J, Huang Y. Validation of a prediction model for intraoperative hypothermia in patients receiving general anesthesia. *Int J Clin Pract*. 2022;2022:6806225.
- [15] Yi J, Zhan L, Lei Y, et al. Establishment and validation of a prediction equation to estimate risk of intraoperative hypothermia in patients receiving general anesthesia. *Sci Rep*. 2017;7:13927.
- [16] Dibiasi C, Agibetov A, Kapral L, Zeiner S, Kimberger O. Predicting intraoperative hypothermia burden during non-cardiac surgery: a retrospective study comparing regression to six machine learning algorithms. *J Clin Med*. 2023;12:4434.
- [17] Ren W, Li D, Wang J, Zhang J, Fu Z, Yao Y. Prediction and evaluation of machine learning algorithm for prediction of blood transfusion during cesarean section and analysis of risk factors of hypothermia during anesthesia recovery. *Comput Math Methods Med*. 2022;2022:8661324.
- [18] Luo H, Xiang C, Zeng L, et al. SHAP based predictive modeling for 1 year all-cause readmission risk in elderly heart failure patients: feature selection and model interpretation. *Sci Rep*. 2024;14:17728.
- [19] Dong M, Huang YH, Zhang YJ, et al. Chinese Medical Association guideline for clinical diagnosis and treatment of lung cancer (2023 edition, Chinese): an interpretation. *Chin J Cardiothoracic Surgery*. 2023;30:1533–8.
- [20] Riley RD, Ensor J, Snell KIE, et al. Calculating the sample size required for developing a clinical prediction model. *BMJ*. 2020;368:m441.
- [21] Hypothermia: Prevention and Management in Adults Having Surgery. London: National Institute for Health and Care Excellence (NICE). 2016;12.
- [22] Lundberg SM, Su-In LA. Unified approach to interpreting model predictions. In: *Proceedings of the 31st International Conference on Neural Information Processing Systems*. Curran Associates Inc. 2017;30:4768–77.
- [23] Wang K, Tian J, Zheng C, et al. Interpretable prediction of 3-year all-cause mortality in patients with heart failure caused by coronary heart disease based on machine learning and SHAP. *Comput Biol Med*. 2021;137:104813.
- [24] Fan Z, Jiang J, Xiao C, et al. Construction and validation of prognostic models in critically ill patients with sepsis-associated acute kidney injury: interpretable machine learning approach. *J Transl Med*. 2020;21:406.
- [25] Knaepel A. Inadvertent perioperative hypothermia: a literature review. *J Perioper Pract*. 2012;22:86–90.
- [26] Huang PP, Mi YY, Wu BN, et al. Evidence summary for the prevention and management of unplanned hypothermia in cancer patients during surgery (Chinese). *J Nurs*. 2018;25:33–9.
- [27] Choi RY, Coyner AS, Kalpathy-Cramer J, Chiang MF, Campbell JP. Introduction to machine learning, neural networks, and deep learning. *Transl Vis Sci Technol*. 2020;9:14.
- [28] Deo RC. Machine learning in medicine. *Circulation*. 2015;132:1920–30.
- [29] Handelman GS, Kok HK, Chandra RV, Razavi AH, Lee MJ, Asadi H. eDoctor: machine learning and the future of medicine. *J Intern Med*. 2018;284:603–19.
- [30] Zeng X, et al. Construction and validation of Intraoperative Hypothermia risk prediction model in lung cancer patients (Chinese). *Chin. Nurs. Manag*. 2023;23:1500–6.
- [31] Yang MF, et al. Study on the rewarming effect of warming transfusion strategy based on guidelines in severe trauma patients with hypothermia (Chinese). *Chin J Emergency Med*. 2018;27:492–8.
- [32] Lu Z, Chen X. Early prediction of intraoperative hypothermia in patients undergoing gynecological laparoscopic surgery: a retrospective cohort study. *Medicine (Baltimore)*. 2024;103:e39038.
- [33] WHO. Hypothermia: Prevention and Management in Adults Having Surgery. National Institute for Health and Care Excellence (NICE). 2016:1.
- [34] Zhao ZH, Xing XM, Feng B, et al. Evidence summary of rewarming management of hypothermia in adult critically ill patients (Chinese). *J Nurs*. 2021;28:39–43.
- [35] Huang LF, et al. A multicentre retrospective study of intraoperative temperature changes in patients undergoing thoracoscopic radical resection of lung cancer (Chinese). *Nurs Res*. 2021;35:4390–3.
- [36] Lenhardt R. Body temperature regulation and anesthesia. *Handb Clin Neurol*. 2018;157:635–44.
- [37] Wang R, Yao M, Sheng H, et al. Construction and validation of a risk prediction model for prolonged post-anesthesia care Unit stay in patients undergoing radical resection of gastrointestinal neoplasms (Chinese). *J Nurs*. 2024;39:55–63.