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Original Article

Various machine learning prediction models for short-term postoperative prognosis of colorectal cancer based on intraoperative hypothermia

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Abstract: This retrospective study aimed to investigate inadvertent intraoperative hypothermia (IIH) in patients undergoing laparoscopic radical resection for colorectal cancer (CRC) and to compare predictive models for short-term prognosis. Among 296 CRC patients (January 2022 to June 2024), univariate and multivariate logistic regression identified independent risk factors. Based on these, five models (nomogram, neural network, decision tree, random forest, gradient boosting machine) were constructed and evaluated using ROC, calibration curves, decision curves, and confusion matrices, with an additional 102 patients (July 2024 to July 2025) for clinical validation. Of the 296 patients, 72 (24.32%) had poor short-term prognosis, and 102 (34.46%) experienced IIH. Restricted cubic spline analysis showed IIH duration >55 minutes significantly increased poor prognosis risk. IIH was an independent risk factor (OR=4.498, P<0.001), remaining significant after adjusting for tumor location, TNM stage, and CEA (OR=4.245, P<0.001). Rectal tumor location, TNM stage III, and CEA ≥5 ng/mL were also risk factors. Except for the decision tree, the four other models showed good predictive performance in both sets. In the independent validation (102 cases), prediction accuracies were 83.33%, 78.43%, 78.43%, 77.45%, and 75.49%, respectively. In conclusion, IIH is an independent risk factor for poor short-term prognosis after laparoscopic CRC resection, with significantly increased risk when duration exceeds 55 minutes. Logistic regression, neural network, random forest, and gradient boosting machine all demonstrate excellent predictive performance.

Keywords: Colorectal cancer, laparoscopic radical surgery, short-term prognosis, inadvertent intraoperative hypothermia, influencing factors

Introduction

Laparoscopic radical surgery has become the main treatment method for colorectal cancer (CRC) due to its advantages such as less trauma and faster recovery [1-3]. However, patients with advanced CRC often experience abnormal defecation functions, and they frequently suffer from decreased appetite, reduced food intake, and accompanied by weight loss and malnutrition [4-6]. This makes patients more prone to various complications during the perioperative period, among which intraoperative hypothermia is a relatively common but often overlooked problem. Inadvertent intraoperative hypothermia (IIH) is not a benign physiological phenomenon [7]. Existing studies have shown that hypothermia can lead to a series of adverse consequences such as delayed drug metabolism, coagulation dysfunction, increased risk of cardiac events, and increased infection rate of surgical incisions [8, 9]. However, previous studies have mostly focused on open surgeries or mixed different surgical types. For this specific group of patients undergoing laparoscopic colorectal cancer surgery, there is still insufficient targeted research on the association between hypothermia and the short-term postoperative prognosis of patients, and the independent effect size still needs to be accurately evaluated after strict control of other confounding factors.

From the perspective of host factors, CRC patients often have malnutrition, weight loss, and systemic inflammatory conditions, especially for patients in the middle and advanced stages, their metabolic reserves and thermo-

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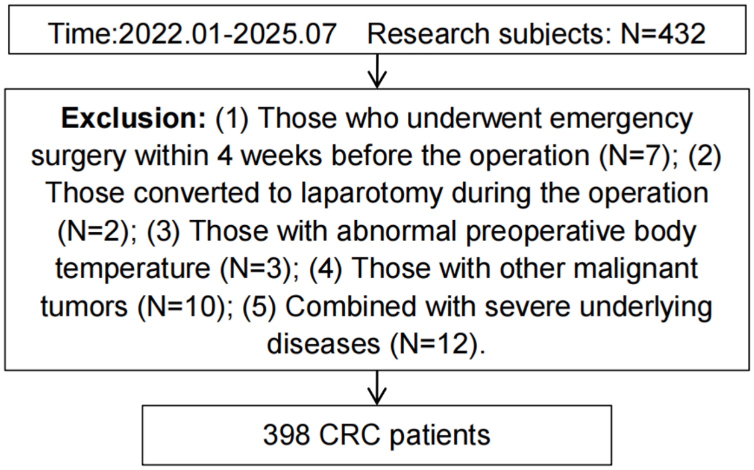

Figure 1. Flowchart of the screening process for patients.

regulation capabilities may have been impaired [10, 11]. From the perspective of surgical factors, laparoscopic operation has a unique heat dissipation pathway: the prolonged maintenance of pneumoperitoneum (usually >2 hours) exposes the abdominal cavity to a low-temperature, dry environment of carbon dioxide, resulting in enhanced convective and evaporative heat loss [10, 11]. In laparoscopic radical resection of CRC patients, the use of room temperature or hypothermia fluids for frequent peritoneal irrigation to obtain a clear surgical field contributes further to conductive heat dissipation to a large extent. In addition, the metal part of the laparoscopic instrument is in direct contact with the patient's body cavity, which can also serve as a route of heat conduction. These factors work together to make patients undergoing laparoscopic colorectal surgery more likely to develop IIH than those undergoing open colorectal surgery.

Based on clarifying the independent harmful effects of IIH on the prognosis of CRC patients, if we can further integrate this key intraoperative variable and other perioperative factors to construct a predictive model that can be used for preoperative or intraoperative early risk stratification, it will have profound clinical significance. Such a model can quantify the prognosis risk of individual patients and provide decision support for the transition from "general prevention" to "precise warning", ultimately guiding the concentration of limited medical resources on high-risk groups and maximizing the improvement of patient outcomes. Therefore, this study aims to focus on patients undergoing laparoscopic radical resection of colorectal cancer, first clarifying the independent association between intraoperative hypothermia and the short-term adverse prognosis of patients, to demonstrate the necessity of active temperature management; then, systematically analyzing the independent risk factors for the occurrence of poor short-term prognosis and constructing the relevant predictive model, in order to provide a reference for improving the surgical prognosis of CRC patients.

Materials and methods

General information

A retrospective study was conducted, and 398 CRC patients who were treated in Taiyuan Central Hospital from January 2022 to July 2025 were selected as the research subjects (**Figure 1**). Inclusion criteria: (1) Age ≥18 years old; (2) The pathological diagnosis is colon cancer or rectal cancer; (3) Receive elective laparoscopic radical surgery treatment; (4) American Society of Anesthesiologists (ASA) classification: I-III; (5) Normal coagulation function. Exclusion criteria: (1) Those who developed acute intestinal obstruction, perforation, etc. within 4 weeks before the operation and required emergency surgery; (2) Those who are converted to laparotomy during the operation; (3) Those with abnormal preoperative body temperature (average body temperature from admission to preoperative <36.0°C or >37.5°C); (4) Those with concurrent other malignant tumors; (5) Severe underlying diseases that may independently affect body temperature regulation or predominate the latter (such as severe thyroid dysfunction, hypothalamic or pituitary diseases, uncontrolled severe systemic infections, Parkinson's disease, etc.). This study was approved by the Ethics Committee of Taiyuan Central Hospital.

Sample size evaluation

The sample size required was calculated based on the principle that the sample size should be no less than 5 to 10 times the number of included variables (Logistic regression model). The number of variables included in this study is 22 (as listed in the "Data Collection" section, these are 22 indicators), so the sample size should be no less than 110-220 cases. Considering the specific situation of CRC patients admitted to Taiyuan Central Hospital, 296 CRC patients were finally included for analysis. According to the principle that the sample size for clinical validation should be no less than 1/4 to 1/2 of the internal validation, an additional 102 patients were collected for clinical validation in this study.

Data collection

In the electronic medical record system of the hospital, the research subjects that meet the inclusion and exclusion criteria were screened, and the clinical data of the research subjects were collected. The collected data included: age, gender, BMI, smoking and drinking history, diabetes, hypertension, tumor location (colon vs. rectum), TNM stage, ASA classification, anesthesia time, operation duration, intraoperative blood loss, preoperative carcinoembryonic antigen (CEA), Carbohydrate antigen (CA) 19-9, CA125, and CA72-4 expression levels, preoperative serum albumin, preoperative hemoglobin, preoperative heart rate, intraoperative room temperature, and warming measures.

IIH and short-term outcomes assessment

(1) The anesthesiologist inserts a temperature probe through the nasal cavity into the nasopharynx to measure the patient's intraoperative body temperature (testing once every 15 minutes). Patients with core body temperature below 36.0°C during the operation are defined as having intraoperative hypothermia.

(2) Collect the postoperative 30-day prognosis of the patients and, based on the relevant standards of ACS NSQIP, define patients who experience the following events within 30 days as having short-term poor prognosis [12, 13]: cardiovascular events, such as myocardial infarction (Electrocardiogram and dynamic changes of myocardial enzymes), heart failure, hemorrhagic or ischemic stroke (Confirmed by imaging); anastomotic leakage, postoperative fever (Core body temperature ≥38° for a single measurement), abdominal pain, peritonitis, sepsis signs, etc.; postoperative bleeding (Hemoglobin drop ≥20 g/L or blood transfusion, or active bleeding confirmed by imaging/endoscopy), such as gastrointestinal bleeding and abdominal cavity bleeding; pulmonary embolism; pulmonary infection; abdominal cavity infection; deep vein thrombosis; gastric emptying disorder, surgical incision infection (Incision redness, exudation, purulent secretion + pathogenic evidence), diarrhea, urinary tract infection (Positive urine culture + urinary tract symptoms or fever), urinary retention; unplanned reoperation, etc. Count the patients who experienced poor prognosis within 30 days as the poor prognosis group, and the remaining patients as the good prognosis group. At the same time, assess the degree of poor prognosis of the patients based on the Clavien-Dindo classification [13].

Model construction and verification

(1) Nomogram Model: ① Using R software, 296 CRC patients were divided into a training set and a validation set in a 7:3 ratio. ② Using univariate analysis, indicators with significant differences between the patients in the poor prognosis group and the good prognosis group were screened ($P<0.05$). The indicators with significant differences between the groups in the univariate analysis were taken as independent variables, and the prognosis status as the dependent variable, and a multivariate Logistic regression analysis was conducted. ③ The indicators with significant differences in the multivariate Logistic regression analysis were visualized to obtain a nomogram prediction model.

(2) Construction of the neural network model: The neural network model consists of an input layer, a hidden layer, and an output layer. Variables that passed the single-factor analysis and had a *P* value less than 0.05 were included in the input layer. The number of nodes in the input layer was equal to the number of included variables. The output layer was a binary classification node for the prognosis outcome (i.e., poor prognosis). The structure of the hidden layer was determined through systematic optimization: a single hidden layer

architecture was adopted, and the number of hidden layer nodes was determined through grid search combined with 5-fold cross-validation. The search range was 1, 2, 3, 5, 10, and the number of input variables. The optimal number of nodes was finally selected based on maximizing the AUC of the validation set. Hyperparameter tuning was performed using random search combined with 5-fold cross-validation, optimizing key hyperparameters: the search range for the learning rate was 0.001 to 0.1, the activation functions were compared between sigmoid, tanh, and ReLU, the dropout ratio was set to 0 to 0.5 to prevent overfitting, and the number of iterations was determined using early stopping (patience =20). The final model used the elastic backpropagation algorithm (Rprop+) or the standard backpropagation algorithm, with a weight decay coefficient of 0.001. Model performance was evaluated using the AUC of the training set and validation set.

(3) Construction of the decision tree model: The CART algorithm is used for the construction of the decision tree, and no pruning operation is performed during the process. The key hyperparameters are determined through 10-fold cross-validation: the maximum depth (maxdepth) of the tree is searched within the range of 3 to 10 layers, and the final determination is based on maximizing the AUC of the validation set and ensuring good model interpretability; the minimum number of samples for splitting nodes (minsplit) is set to 20 to ensure that each splitting node has sufficient statistical power; the minimum number of samples for leaf nodes (minbucket) is set to 7 (approximately 1/3 of minsplit); the complexity parameter (cp) is set to 0, allowing the tree to grow fully until it meets the above constraints. The calculation is performed using the rpart software package, and the splitting feature is selected based on the criterion of minimizing the Gini coefficient, generating a binary tree consisting of root nodes, internal nodes, and leaf nodes. The model is evaluated for generalization performance through 10-fold cross-validation, reporting the average AUC and its 95% confidence interval, and final performance verification is conducted on the independent validation set.

(4) Construction of the Random Forest Model: In the R 4.2.1 environment, the model is constructed by calling the randomForest package. The key hyperparameters are systematically optimized through grid search combined with 5-fold cross-validation, using out-of-bag (OOB) error and validation set AUC as evaluation metrics: mtry (the number of variables randomly selected for each tree) has a search range of 2, the square root of the total number of variables, 1/3 and 1/2 of the total number of variables, and is finally determined based on the minimum OOB error; ntree (the number of trees) is determined by plotting the OOB error curve as a function of tree number, with an initial search range of 100 to 2000 (step size 100), and the minimum number of trees with a stable OOB error is selected; the minimum number of samples for node splitting (nodesize) is set to 5 to control the complexity of a single tree; the maximum depth (maxdepth) is set to 30 to prevent a single tree from growing excessively. The average Gini index of each variable is calculated based on the optimal hyperparameter combination, and a random forest prediction model for poor prognosis of CRC patients is established based on this ranking. The model is tuned on the training set and evaluated for final performance on the independent validation set.

(5) Construction of the gradient boosting machine (GBM) model: The forward stepwise additive modeling approach is adopted. In each iteration, a new decision tree is fitted based on the negative gradient (pseudo-residual) predicted by the current model, and the model is updated with the set learning rate, gradually reducing the overall loss function (log loss). The key hyperparameters are optimized using grid search combined with 10-fold cross-validation, with the log loss of the validation set and AUC as evaluation metrics: The search range for the number of iterations (n.trees) is 100 to 5000 (step size 100), and the iteration number with the lowest log loss in the validation set is selected; the learning rate (shrinkage) is set to 0.01 or 0.001, and the optimal value is determined through comparative experiments; the tree depth (interaction.depth) search range is 1 to 10, controlling the complexity of feature interaction; the sub-sampling ratio (bag.fraction) search range is 0.5 to 0.8, introducing randomness to prevent overfitting; the minimum split sample number (n.minobsinnode) is

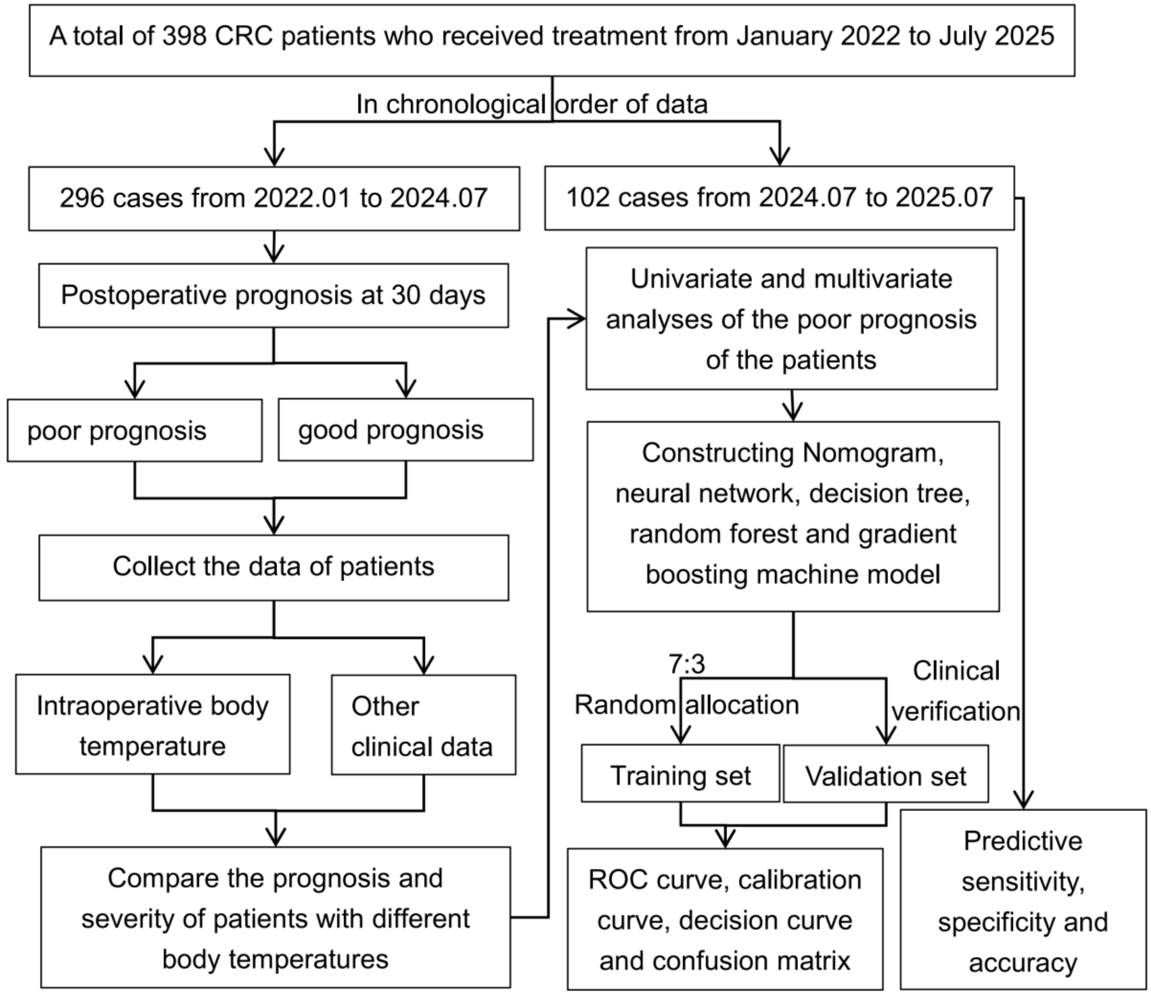

Figure 2. Research flowchart. CRC: colorectal cancer, ROC: receiver operator characteristic.

set to 10 to control the size of terminal nodes. To determine the optimal model complexity and prevent overfitting, the generalization error of the model under different numbers of iterations is evaluated using 10-fold cross-validation, and the iteration number with the smallest validation error is selected as the number of trees for the final model. After model training, the relative influence of each feature in the tree split is analyzed to evaluate and rank the relative importance of each input variable for the prediction result. Finally, performance evaluation is conducted on the training set and the independent validation set.

(6) Model Validation: ① Internal validation: The predictive value of the model for the short-term prognosis of CRC patients was tested in the training set and the validation set using Receiver characteristic curve (ROC), calibration curve and decision curve. ② Clinical validation: Another 102 CRC patients who received treatment in Taiyuan Central Hospital from July 2024 to July 2025 were selected as the clinical validation subjects. The accuracy of the model's prediction was tested using the confusion matrix. The technical route of the study is shown in **Figure 2**.

Statistical analysis

Data analysis was conducted using SPSS 26.0 software and R 4.5.1. For measurement data that followed a normal distribution, the mean ± standard deviation was used to represent them, and t-tests were employed for com-

Table 1. Basic characteristics of the research subjects

Index	Training set (n=207)	Validation set (n=89)	Clinical validation set (n=102)	χ^2	P
Age (years)				4.589	0.101
>60	94 (45.41%)	29 (32.58%)	39 (38.24%)		
≤60	113 (54.59%)	60 (67.42%)	63 (61.76%)		
Gender				1.034	0.596
Male	118 (57.00%)	48 (53.93%)	52 (50.98%)		
Female	89 (43.00%)	41 (46.07%)	50 (49.02%)		
BMI (kg/m^2)				2.073	0.355
>24.0	141 (68.12%)	53 (59.55%)	68 (66.67%)		
≤24.0	66 (31.88%)	36 (40.45%)	34 (33.33%)		
Smoking				1.238	0.539
Yes	63 (30.43%)	22 (24.72%)	32 (31.37%)		
No	144 (69.57%)	67 (75.28%)	70 (68.63%)		
Drinking				1.563	0.458
Yes	56 (27.05%)	18 (20.22%)	25 (24.51%)		
No	151 (72.95%)	71 (79.78%)	77 (75.49%)		
T2DM				0.762	0.683
Yes	65 (31.40%)	24 (26.97%)	33 (32.35%)		
No	142 (68.60%)	65 (73.03%)	69 (67.65%)		
Hypertension				2.019	0.364
Yes	90 (43.48%)	31 (34.83%)	40 (39.22%)		
No	117 (56.52%)	58 (65.17%)	62 (60.78%)		
Tumor location				3.33	0.189
Colon	124 (59.90%)	49 (55.06%)	50 (49.02%)		
Rectal	83 (40.10%)	40 (44.94%)	52 (50.98%)		
TNM				0.914	0.633
Phase III	77 (37.20%)	28 (31.46%)	37 (36.27%)		
Phase I-II	130 (62.80%)	61 (68.54%)	65 (63.73%)		

Note: BMI: Body Mass Index, T2DM: Type 2 diabetes, TNM: tumor node metastasis.

parisons between groups. For categorical variables, n (%) was used to represent them, and chi-square tests were employed for comparisons between groups; when the data were in a ranked distribution, rank sum tests were used. Logistic regression analysis was employed to explore the association between intraoperative hypothermia and short-term adverse prognosis in CRC patients, after adjusting for confounding factors. Restricted cubic spline (RCS) regression curve was used to fit the relationship between the duration of IIH and postoperative short-term poor prognosis. Using the R software, five prediction models were constructed respectively: the nomogram model, the neural network model, the decision tree model, the random forest model, and the gradient boosting machine model. $P<0.05$ was considered statistically significant.

Results

Characteristics and short-term prognosis of the research subjects

As shown in **Table 1**: among the 296 CRC patients included in the study and used for model construction and internal validation (Training set and Validation set), 166 (56.08%) were male and 130 (43.92%) were female; 123 (41.55%) were over 60 years old and 173 (58.45%) were 60 years old or younger; 89 (30.07%) had T2DM and 207 (69.93%) did not. In the 102 CRC patients used for clinical validation (Clinical validation set), 52 (50.98%) were male and 50 (49.02%) were female; 39 (38.24%) were over 60 years old and 63 (61.76%) were 60 years old or younger; 33 (32.35%) had T2DM and 69 (67.65%) did not.

Table 2. Comparison of clinical outcomes among patients with different body temperature conditions

Temperature	Total	I	II	III	IV
Hypothermia (n=102)	44 (43.14)	9 (8.82)	27 (26.47)	6 (5.88)	2 (1.96)
Normothermia (n=194)	28 (14.43)	14 (7.22)	12 (6.19)	2 (1.03)	0 (0.00)
χ^2/Z	24.123		-2.636		
P	<0.001		0.008		

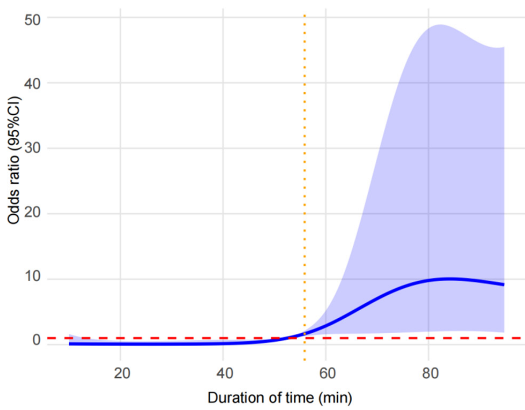

Figure 3. Restricted cubic spline curve of IIH duration and poor short-term postoperative prognosis. IIH: inadvertent intraoperative hypothermia.

The occurrence and prognosis of IIH in the research subjects

Based on the intraoperative temperature monitoring results, among the 296 patients, 102 (34.46%) experienced IIH. According to the follow-up data of the patients 30 days after the operation, 72 (24.32%) of the 296 patients had poor short-term prognosis. As shown in **Table 2**, there was a great difference in the overall poor prognosis between patients with IIH and those with normal body temperature ($P<$ 0.001). 23 cases of grade I complications, including diarrhea (8 cases), urinary retention (8 cases), and unexplained fever (7 cases), were all relieved after symptomatic treatment. 39 cases had grade II complications, mainly manifested as deep vein thrombosis (5 cases), pulmonary infection (13 cases), abdominal infection (7 cases), gastric emptying disorder (3 cases), intestinal obstruction (3 cases), surgical incision infection (3 cases), and urinary tract infection (5 cases), all of which improved after corresponding drug treatment or intervention. 8 cases had grade III complications, including 5 cases of anastomotic leakage (emergency colostomy surgery) and 3 cases of postoperative bleeding (emergency surgical hemostasis). 2 patients had grade IV complications (heart failure, requiring circulatory support treatment).

RCS curve of IIH duration and poor short-term postoperative prognosis

To further explore the effect of the duration of intraoperative hypothermia on the short-term prognosis of patients, the RCS regression model was used to fit the relationship between the total duration of intraoperative hypothermia below 36° and the poor short-term prognosis after surgery. The analysis results of the RCS curve shown in **Figure 3** indicate that the duration of IIH has a significant overall predictive value for the short-term prognosis of patients (Overall association $P<0.001$), suggesting that this variable is an important influencing factor for the short-term prognosis. Although the strict non-linear test did not reach a significant level (Non-linearity $P=0.056$), it was close to the significance threshold (0.05), and the shape of the RCS curve suggests an approximate threshold effect: when the duration of IIH is greater than 55 minutes, it significantly increases the risk of poor short-term prognosis for patients.

Univariate analysis of the impact on patients' short-term prognosis

As shown in **Table 3** of the univariate analysis, there were significant differences in the short-term prognosis of patients with different intraoperative body temperatures, tumor locations, tumor stages, and CEA levels (all P<0.05); the short-term prognosis of patients with other characteristics was similar (all P>0.05).

Multivariate analysis of factors influencing the short-term prognosis of patients

The prognosis of patients was taken as the dependent variable (1= poor prognosis, 0= good prognosis), and the indicators that might

Table 3. Univariate analysis of the impact on patients' short-term prognosis

Index	Poor prognosis (n=72)	Good prognosis (n=224)	χ^2/t	*P*
Temperature			29.923	<0.001
Hypothermia	44 (43.14%)	58 (56.86%)		
Normothermia	28 (14.43%)	166 (85.57%)		
Age (years)			2.795	0.095
>60	36 (29.27%)	87 (70.73%)		
≤60	36 (20.81%)	137 (79.19%)		
Gender			2.155	0.142
Male	35 (21.08%)	131 (78.92%)		
Female	37 (28.46%)	93 (71.54%)		
BMI (kg/m^2)			1.180	0.277
>24.0	51 (26.29%)	143 (73.71%)		
≤24.0	21 (20.59%)	81 (79.41%)		
T2DM			3.521	0.061
Yes	28 (31.46%)	61 (68.54%)		
No	44 (21.26%)	163 (78.74%)		
Hypertension			0.187	0.666
Yes	31 (25.62%)	90 (74.38%)		
No	41 (23.43%)	134 (76.57%)		
Smoking			0.157	0.692
Yes	22 (25.88%)	63 (74.12%)		
No	50 (23.70%)	161 (76.30%)		
Drinking			0.881	0.348
Yes	21 (28.38%)	53 (71.62%)		
No	51 (22.97%)	171 (77.03%)		
Tumor location			10.735	0.001
Rectal	54 (31.21%)	119 (68.79%)		
Colon	18 (14.63%)	105 (85.37%)		
TNM			4.462	0.035
Phase III	33 (31.43%)	72 (68.57%)		
Phase I-II	39 (20.42%)	152 (79.58%)	2.148	0.143
ASA classification				
Grade III	34 (28.81%)	84 (71.19%)	2.148	0.143
Grade I-II	38 (21.35%)	140 (78.65%)		
Anesthesia duration (min)	201.90±521.32	198.75±27.82	1.209	0.228
Surgery duration (min)	174.69±27.82	168.17±23.32	1.796	0.075
Intraoperative blood loss (mL)			0.025	0.873
>150	19 (25.00%)	57 (75.00%)		
≤150	53 (24.09%)	167 (75.91%)		
CEA			17.042	<0.001
≥5 ng/mL	47 (35.88%)	84 (64.12%)		
<5 ng/mL	25 (15.15%)	140 (84.85%)		
CA19-9			0.230	0.631
≥37 U/mL	26 (26.00%)	74 (74.00%)		
<37 U/mL	46 (23.47%)	150 (76.53%)		
CA125			1.437	0.231
≥35 U/mL	20 (29.85%)	47 (70.15%)		
<35 U/mL	52 (22.71%)	177 (77.29%)		

CA72-4			0.213	0.645
≥6.9 U/mL	17 (22.37%)	59 (77.63%)		
<6.9 U/mL	55 (25.00%)	165 (75.00%)		
Preoperative serum albumin			0.115	0.735
<35 g/L	26 (25.49%)	76 (74.51%)		
≥35 g/L	46 (23.71%)	148 (76.29%)		
Preoperative hemoglobin			2.364	0.124
Anemia*	33 (29.20%)	80 (70.80%)		
Normal	39 (21.31%)	144 (78.69%)		
Preoperative heart rate	72 (67,77)	72 (68,77)	0.048	0.962
Intraoperative room temperature	21.60±0.89	21.58±1.09	0.108	0.914
Warming measures			1.167	0.280
Quilt	23 (28.75%)	57 (71.25%)		
Quilt + others	49 (22.69%)	167 (77.31%)		

Note: *female <110 g/L, male <120 g/L, ASA: American Society of Anesthesiologists, CEA: carcinoembryonic antigen, CA19-9: Carbohydrate antigen 19-9, CA125: Carbohydrate antigen 125, CA72-7: Carbohydrate antigen 72-4.

Table 4. Variable assignment

Variable	Variable assignment
Dependent variable	
prognosis	1= poor prognosis, 0= good prognosis
Independent variable	
IIH	1= Yes, 0= No
Tumor location	1= rectal, 0= colon
TNM	1= phase III, 0= phase I-II
CEA	1="≥5 ng/mL", 0="<5 ng/mL"

Table 5. Correlation analysis between IIH and short-term prognosis of patients

Variable	β	SE	Wald χ^2	P	OR	95% CI
Equation 1						
IIH	1.504	0.286	27.667	<0.001	4.498	2.568-7.876
Equation 2						
IIH	1.446	0.303	22.747	<0.001	4.245	2.343-7.689
Rectal cancer	1.056	0.331	10.198	0.001	2.876	1.504-5.501
Phase III	0.613	0.307	3.981	0.046	1.847	1.011-3.374
CEA≥5 ng/mL	1.143	0.308	13.783	<0.001	3.135	1.715-5.730
Constant	-3.273	0.413	62.654	-	-	-

Note: Equation 1 only included intraoperative hypothermia, while Equation 2 adjusted for variables such as tumor location, TNM stage, and CEA. OR: Odds Ratio.

affect the prognosis of CRC patients were taken as independent variables. Logistic regression analysis was used to explore the association between intraoperative hypothermia and the prognosis of patients (the assignment of each variable is shown in **Table 4**). As shown in **Table 5**: The result of Equation 1 indicates that when only considering the relationship between IIH and the prognosis of patients, IIH was an independent risk factor for poor prognosis in CRC patients (OR=4.498, P<0.001). The result of Equation 2 indicates that after correcting for factors such as tumor location, TNM stage, and CEA, IIH remained an indenpendent risk factor for poor prognosis in CRC patients (OR=4.245, P<0.001). At the same time, the result of Equation 2 also shows that, except for IIH, rectal cancer, TNM stage III, and CEA ≥5 ng/mL are also risk factors for poor short-term prognosis of CRC patients (OR are 2.876, 1.847, and 3.135 respectively, all P<0.05).

Construction and validation of a nomogram model for short-term poor prognosis in CRC patients under laparoscopy

The results of the above multivariate Logistic regression analysis were visualized to obtain the nomogram model shown in **Figure 4**. The nomogram model consists of various influencing factors and corresponding certain-length line segments (in this study, IIH, tumor location, TNM stage, and CEA). Researchers can

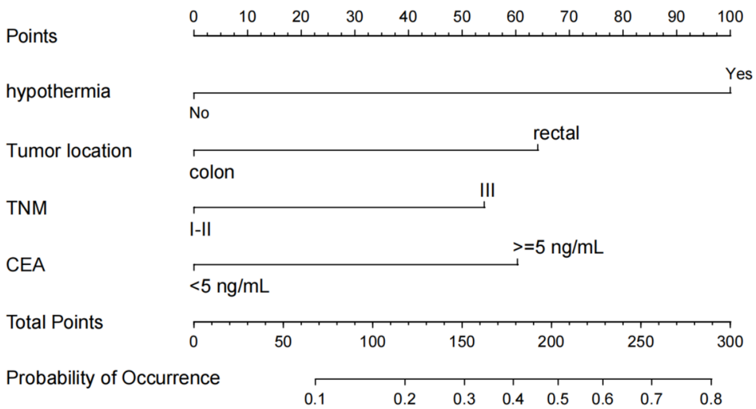

Figure 4. The nomogram model for predicting poor short-term prognosis. TNM: tumor node metastasis, CEA: carcinoembryonic antigen.

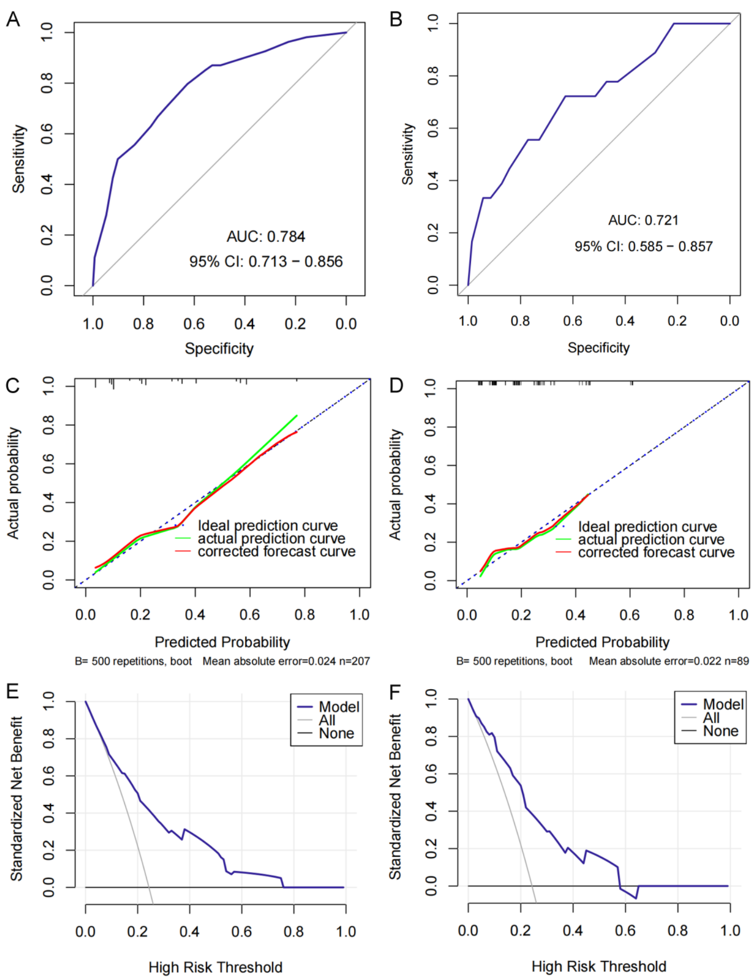

Figure 5. Test of the nomogram model. A. AUC of the training set; B. AUC of the validation set; C. Calibration curve of the training set; D. Calibration curve of the validation set; E. Decision curve of the training set; F. Decision curve of the validation set.

obtain the score of each individual influencing factor based on the specific circumstances of the subjects, and the sum of the scores of multiple influencing factors can be used to obtain the total score of the subject. On the total score axis, draw a perpendicular line downward to obtain the risk value of poor prognosis for the subject. **Figure 5A**, **5B** show that the ROC values of the model in the training set and validation set were 0.784 (95% CI: 0.713-0.856) and 0.721 (95% CI: 0.585-0.857), respectively. The calibration curve analysis in **Figure 5C**, **5D** revealed that there was no great difference between the prediction curves of the model and the calibration curves in both the training set and validation set (all P>0.05), and the Mean absolute error was 0.024 and 0.022, respectively. The decision curve test in **Figure 5E**, **5F** shows that, based on the incidence of intraoperative hypothermia of 24.32%, in the training set, the benefit rate of the model was higher than the "All" curve and the "None" curve at the probability threshold of 8% to 77%; in the validation set, at the probability threshold of 4% to 58%, the benefit rate of the model was higher than the "All" curve and the "None" curve. The "All" curve refers to intervening all patients (even if there is no risk of poor prognosis), in which case the net benefit decreases as the threshold increases (due to excessive intervention); the "None" curve refers to not intervening any patients, in which case the net benefit is always 0. As shown in the confusion matrix results in **Figure 8**, the accuracy, sensitivity and specificity of the model in the training set for predicting intraoperative hypothermia were 79.71% (165/207), 90.20% (138/153) and 50.00% (27/54), re-

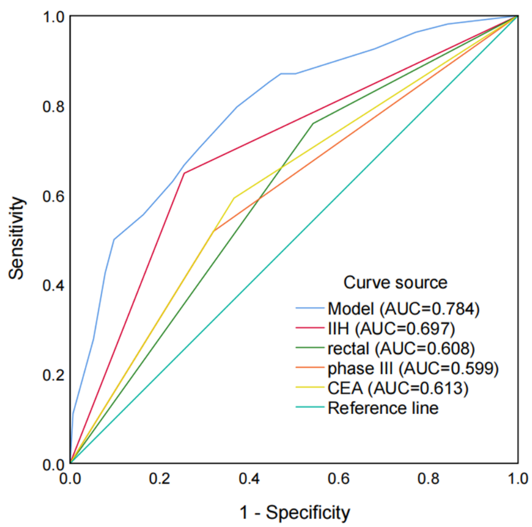

Figure 6. ROC curves of different indicators for predicting poor short-term prognosis of patients.

spectively. 79.78% (71/89), 91.55% (65/71) and 33.33% (6/18) in the validation cohort.

The predictive value of different indicators for prognosis in CRC patients

The ROC curves of different indicators to predict the short-term prognosis of CRC patients are shown in **Figure 6** below. The AUCs of the model, IIH, tumor location, TNM stage and CEA level in predicting poor short-term prognosis of CRC patients were 0.784, 0.697, 0.608, 0.599 and 0.613, respectively, and only the AUC of the model was >0.7. As shown in **Table 6**, the DeLong test results showed that the AUC of the model was significantly higher than the AUC of each index, and the Z values were 3.359, 4.572, 4.037 and 3.909, respectively, all P<0.05.

Construction and validation of the neural network model

As shown in **Figure 7A**, the input layer of the constructed neural network contains 4 nodes, corresponding to the 4 variables in the multiple factor regression analysis. The importance analysis of the neural network model prediction results in **Figure 7B** shows that the order of importance of each index in influencing the prognosis of CRC patients is: Tumor location, CEA, TNM, and hypothermia. As shown in **Figure 7C**, **7D**, the ROC of the neural network model in the training set is 0.780 (95% CI=0.707-0.853), and the ROC in the validation set is 0.786 (95% CI=0.667-0.8957).

Construction and validation of decision tree model

As shown in **Figure 8A**, in this study, the decision tree model is based on the principle of recursive feature splitting, and the feature with the highest information gain is prioritized for node splitting. Eventually, an interpretable tree structure is generated. IIH is the root node feature, indicating its greatest impact on the classification result; among the secondary features, the tumor location is further refined without stratification for patients without IIH. The ROC curve results of the decision tree model are shown in **Figure 8B**, **8C** below. The AUC of the model in the training set and validation set is 0.722 (95% CI=0.645-0.799) and 0.620 (95% CI=0.486-0.755), respectively.

Construction and validation of random forest model

In the random forest model, through the analysis of variable importance, it is found (**Figure 9A**) that intraoperative hypothermia ranks first in both the average reduction accuracy and the average reduction Gini index, and is a key factor for predicting poor prognosis in CRC patients. The ROC curve results of the random forest model are shown in **Figure 9B**, **9C**. The AUC of the model in the training set and validation set is 0.751 (95% CI=0.672-0.830) and 0.774 (95% CI=0.653-0.895), respectively.

Construction and validation of the gradient boosting model

The optimal number of iterations was selected through 10-fold cross-validation. When n. trees=3500, the model had the smallest generalization error (as shown in **Figure 10A**). As shown in **Figure 10B**, the relative importance of various clinical features was obtained using the GBM algorithm, from largest to smallest, they were intraoperative hypothermia, CEA, TNM, and Tumor local. The ROC curve results of the gradient boosting model are shown in **Figure 10C**, **10D**. The AUC of the model in the training set and validation set was 0.769 (95% CI=0.695-0.844) and 0.803 (95% CI=0.697-0.910), respectively.

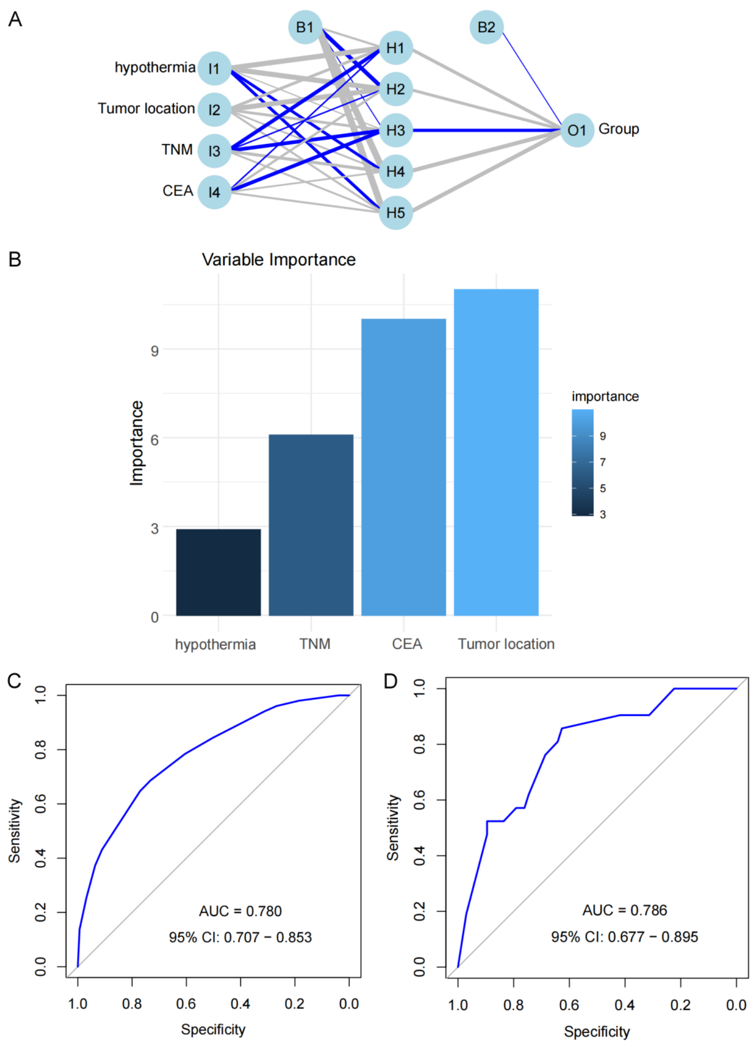

Figure 7. Construction and verification of the neural network model. A. Neural network diagram; B. Ranking of independent variable importance; C. ROC test of the training set; D. ROC test of the validation set.

Comparison of prediction efficacy of different models

As shown in **Table 7**, in the comparison of ROC, the AUC ranking of each model in the training set is: nomogram > neural network > GBM > random forest > decision tree. The DeLong test result shows that there is no significant difference in AUC among all models (all P>0.05). In the validation set, the AUC ranking of each model is: GBM > neural network > random forest > nomogram > decision tree. The DeLong test result shows that the AUC of GBM is significantly higher than that of other models (P<0.05).

Comparison of prediction accuracy of different models

As shown in **Table 8**, in the clinical validation, among the 102 study subjects, 26 cases had poor short-term prognosis, accounting for 25.49%. The accuracy of the constructed nomogram model, neural network model, decision tree model, random forest model, and gradient boosting machine model in predicting the short-term poor prognosis of CRC patients was 83.33% (85/102), 78.43% (80/102), 78.43% (80/102), 77.45% (79/102), and 75.49% (77/102), respectively.

Discussion

According to data from the National Center for Health Statistics (NCHS) of the United States, CRC ranks second among cancer causes of death in the country. In 2023, over 150,000 patients were diagnosed with colorectal cancer, and more than 50,000 of them died [13]. Data from the Global Health Epidemiology Research Group (GHERG) show that the age-standardized incidence rate (ASIR) of colorectal cancer in China has risen from 2.75 to 19.39 (per 100,000 person-years), and it shows a trend of younger onset [14, 15]. Because CRC usually has no specific symptoms in the early stage, changes in defecation habits and stool consistency (such as increased frequency of defecation without obvious causes, thinning stools, bloody stools, mucus stools, etc.) do not occur until the middle or late stage. By the time patients seek medical attention, the disease has often progressed to the middle or late stage and requires surgical treatment [16-18]. However, surgical treatment, as a stressor, is usually accompanied by a series of risks of perioperative complications [19]. These complications not only increase the suffering and medical

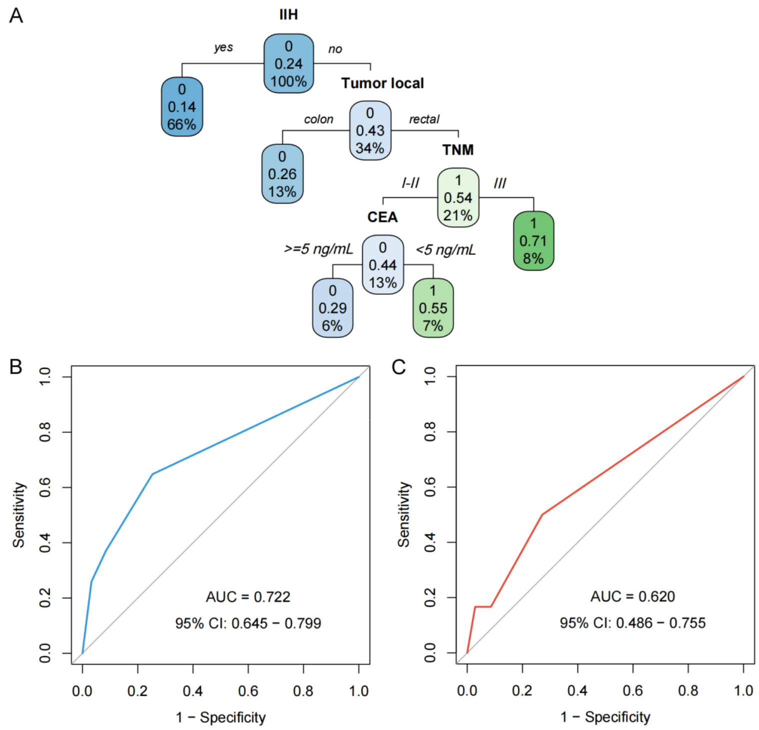

Figure 8. Construction and verification of the decision tree model. A. Decision tree model; B. ROC test of the training set; C. ROC test of the validation set.

Table 6. Predictive value of different indicators for prognosis in patients

Index	AUC	SE	95% CI	Z	P
Model	0.784	0.036	0.713-0.856	/	/
IIH	0.697	0.037	0.629-0.758	3.359	0.001
Rectal cancer	0.608	0.036	0.538-0.675	4.572	<0.001
Phase III	0.599	0.039	0.529-0.666	4.037	<0.001
CEA≥5 ng/mL	0.613	0.039	0.543-0.680	3.909	0.001

Note: AUC: Area Under The Curve.

burden of CRC patients, but also may adversely affect the postoperative recovery and quality of life of patients. Therefore, reducing the occurrence of poor prognosis after laparoscopic radical resection of CRC is of great significance to improve the quality of life of patients.

Among 296 cases included in this study, 72 cases had poor prognosis after surgery, with an incidence of 24.32%. This result is similar to the data reported in previous studies [20-23]. Previous studies have reported that the incidence of intraoperative hypothermia ranges from 19% to 57% [24, 25]. In this study, when analyzing the occurrence of IIH in patients, it was found that 102 cases (34.46%) experienced intraoperative hypothermia. This rate is considered moderately low in previous reports, and it may be related to the better warming measures in the operating room of Taiyuan Central Hospital. The human core temperature is controlled by the subthalamic thermoregulatory center, which is regulated by a negative feedback mechanism, and anesthetic drugs can impair the regulatory effect of this mechanism [26]. Under the stress state of general anesthesia surgery, hypothermia of patients will lead to decreased stability of internal environment and decreased adaptability of the body, which will subsequently have a negative impact on the surgical effect, prognosis and length of hospital stay of patients, and also increase the risk of postoperative complications to a certain extent [27]. The results of this study show that there are significant differences in the degree of poor prognosis among patients with different intraoperative body temperatures. Among them, the severity of postoperative complications in patients who experienced IIH during the operation was significantly higher than that in patients who did not have IIH. The RCS curve analysis of the duration of hypothermia in IIH patients showed that when the duration of IIH was greater than 55 minutes, it significantly increased the risk of poor short-term prognosis for the patients.

The analysis of this study found that intraoperative hypothermia was an independent risk factor for poor short-term prognosis of patients. After adjusting for factors such as tumor location, TNM stage and CEA level, intraoperative hypothermia remained an independent risk factor for poor prognosis of CRC patients (OR=4.245). This result suggests that intraoperative

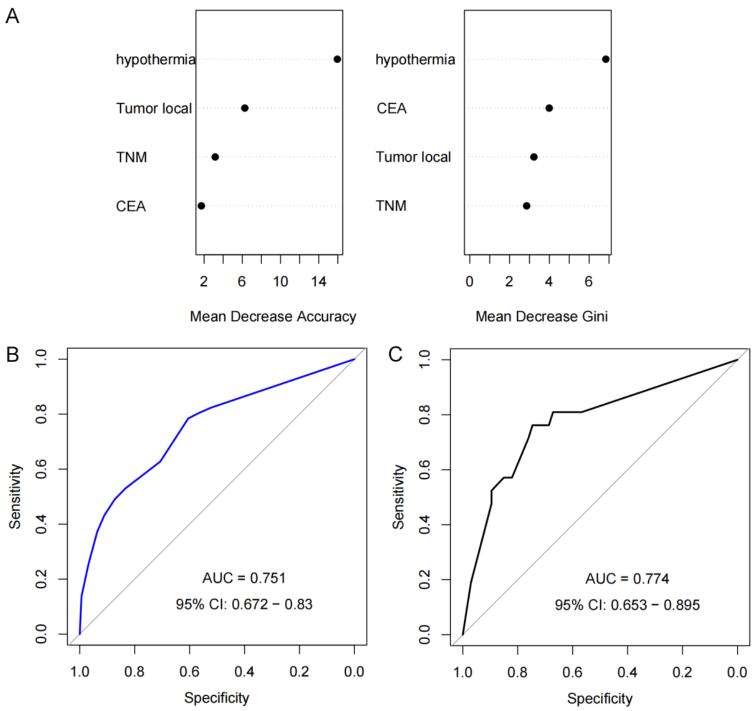

Figure 9. Construction and validation of the random forest model. A. Variable importance ranking of the random forest model; B. ROC test of the training set; C. ROC test of the validation set.

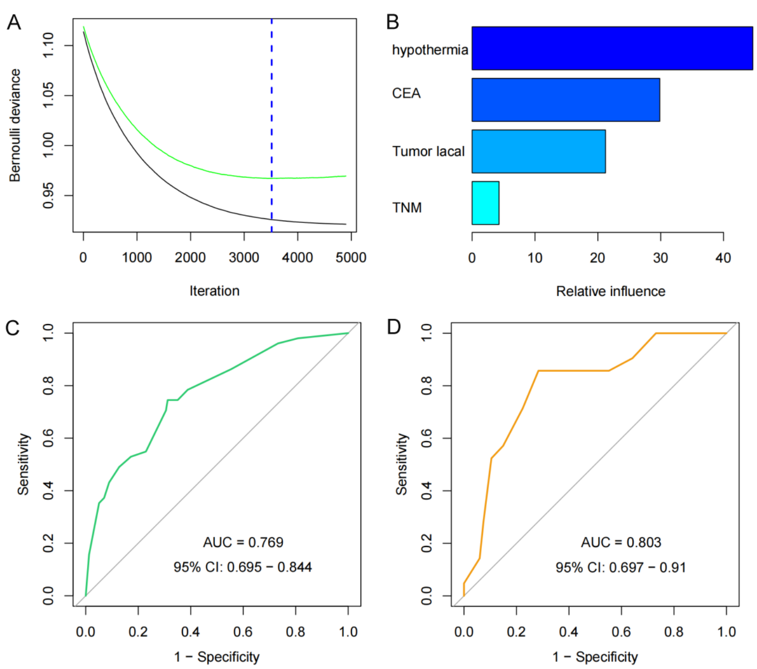

Figure 10. Construction and validation of the gradient boosting machine model. A. Number of iterations; B. Ranking of the relative importance of each variable; C. ROC test of the training set; D. ROC test of the validation set.

hypothermia may be associated with the short-term prognosis of CRC patients after surgery. The underlying mechanism may be related to the multiple effects of hypothermia on the physiological function of the body. Hypothermia can delay drug metabolism, prolong the action time of anesthetic drugs and postoperative analgesics, and then affect the speed of postoperative recovery of patients [28, 29]. Hypothermia can interfere with coagulation function and increase the risk of surgical bleeding and postoperative thrombosis, which will not only prolong the operation time, but also increase the incidence of postoperative complications such as infection [30]. In this study, even though all patients had normal coagulation function before surgery, intraoperative hypothermia still showed a strong association with poor short-term prognosis (OR=4.245), suggesting that intraoperative hypothermia is sufficient to have a significant negative effect on postoperative recovery by affecting physiological processes such as coagulation. Hypothermia may also inhibit the function of the immune system and reduce the body's resistance to infection, thereby increasing the risk of postoperative infection [31]. Together, these factors may lead to delayed postoperative recovery, poor short-term prognosis, and even affect the long-term prognosis of patients.

This study found that intraoperative hypothermia would affect the short-term prognosis of patients together with tumor location, TNM stage and CEA. The rectum is deeply located in the pelvic cavity, the

Table 7. Comparison of prediction efficacy of different models

Model	Data set	
	Training set	Validation set
Nomogram	0.784	0.721
Neural network	0.780	0.786
Decision tree	0.722	0.620
Random forest	0.751	0.774
Gradient boosting machine	0.769	0.803

Table 8. Clinical validation of the model

Model	Predicted by the model (prognosis)	Actual prognosis situation		Total
		Good prognosis	Poor prognosis	
Nomogram	good	67	8	75
	poor	9	18	27
	Total	76	26	102
Neural network	good	66	12	78
	poor	10	14	24
	Total	76	26	102
Decision tree	good	63	9	72
	poor	13	17	30
	Total	76	26	102
Random forest	good	66	13	79
	poor	10	13	23
	Total	76	26	102
Gradient boosting machine	good	62	11	73
	poor	14	15	29
	Total	76	26	102

surgical space is narrow, and it is adjacent to important nerves, blood vessels and urogenital organs, which makes radical resection of rectal cancer more challenging at the technical level [32]. In order to avoid the damage of pelvic autonomic nerve during the operation, it may affect the completeness of the operation. However, in order to pursue the curative effect, it may increase the risk of nerve injury, leading to postoperative urination and sexual dysfunction, and affecting the early recovery quality of patients [33]. In addition, the blood supply of the lower rectum is relatively poor, especially when the anastomosis is in a low position, and the local blood supply may not be sufficient to support good healing, thus significantly increasing the risk of anastomotic leakage as a serious complication. Therefore, patients with tumors located in the rectum may be at higher risk for poor prognosis compared with patients with tumors located in the colon. The results of this study are similar to those reported by Abe et al. [34], in which Abe pointed out that patients with rectal cancer have a higher risk of sarcopenia after surgery compared with patients with colon cancer.

Stage III colorectal cancer means that the tumor has undergone regional lymph node metastasis, which is not only a direct reflection of the invasive biological behavior of the tumor, but also indicates that there may be micrometastases in the patient's body that cannot be detected by clinical imaging. Such patients are often associated with a higher tumor burden and a more active systemic inflammatory state, which may suppress the body's immune function, impair tissue repair, and create a microenvironment conducive to infection and complications. From the perspective of surgery, in order to achieve radical resection (R0 resection) and complete standardized lymph node dissection, stage III patients often need to undergo a wider range and longer operation time, which inevitably causes greater surgical trauma and stronger physiological stress response, thus delaying the postoperative rehabilitation process. Therefore, patients with stage TNM-III may have a higher risk of poor short-term prognosis than patients with stage I-II.

As a classic tumor-associated glycoprotein, the increase of CEA serum level is usually closely related to the increase of tumor burden, poor differentiation and enhanced invasion and metastasis potential [35]. High levels of CEA may not only be directly involved in malignant processes such as tumor cell adhesion, immune escape and angiogenesis, but also reflect the existence of systemic inflammatory state related to tumor [36]. This chronic inflammatory state can lead to immune dysfunction and affect the intrinsic ability of wound healing and tissue repair, making patients more susceptible to complications such as infection and anastomotic leakage after major surgery [37]. In addition, elevated preoperative CEA often suggests the possible presence of micrometastases or minimal residual disease that is difficult to detect on imaging, which may be activated after surgical stress, resulting in recurrence - or metastasis-related events early after surgery. Therefore, preoperative CEA level, as an easy-to-obtain serological index, has a good predictive value for the outcome of patients after surgery, and its increase warns that these patients need more active and rigorous perioperative management.

This study constructed and compared five different predictive models based on four core variables: IIH, tumor location, TNM staging, and CEA level. The results showed that, except for the decision tree model, nomogram, neural networks, random forests, and GBM models all exhibited good predictive performance in both internal and external clinical validations, with AUC values above 0.7. However, there are differences in the performance of different models on the validation set and the ranking of variable importance, which provides an opportunity for us to gain a deeper understanding of model characteristics. Firstly, regarding the difference in model performance, the decision tree model performed significantly worse than other models with an AUC of only 0.620 in the validation set. This phenomenon may be attributed to the characteristics of the decision tree algorithm itself. Specifically, the poor performance of the decision tree can be attributed to the following aspects [38]: First, the decision tree algorithm has a high variance characteristic. With a limited sample size (207 cases in the training set in this study), it is highly sensitive to minor fluctuations and outliers in the training data, easily capturing non-universal data features and leading to overfitting. Second, there may be complex nonlinear interactions among the four predictive variables and the prognosis outcome in this study. For instance, the impact of intraoperative hypothermia on prognosis may vary depending on the TNM stage, and the decision tree, which splits data based on a single feature at each level, is inefficient in modeling such high-order interactions. In a limited sample size, deeper tree structures are even more difficult to estimate stably. Third, compared with ensemble learning methods such as random forests and gradient boosting machines, a single decision tree lacks the mechanism of reducing variance through the integration of multiple models, thus inherently being at a disadvantage in terms of generalization stability, resulting in a significant difference in AUC between the training set and the validation set.

In contrast, neural networks and GBM performed well in the validation set (AUC of 0.786 and 0.803, respectively). Neural networks, through their multi-layer structure and nonlinear activation functions, can automatically learn high-order interactions between input features, thereby more finely characterizing the complex combination effects of IIH, tumor location, TNM staging, and CEA on prognosis. For example, IIH may have a synergistic amplification effect on patients with rectal cancer and elevated CEA, and neural networks can effectively capture such nonlinear relationships. GBM, as an ensemble learning method, iteratively generates a series of weak classifiers (usually decision trees) and combines them to gradually focus on difficult to predict samples, thereby reducing bias while also effectively controlling variance [39]. In this study, after cross validation, the GBM model selected the optimal number of trees for 3500 iterations, effectively avoiding overfitting and ensuring its stability and high discrimination on the validation set. Random forest, as an ensemble model, reduces the variance of the model by introducing randomness in samples and features, thus maintaining robust performance in the validation set. The nomogram model essentially visualizes the results of logistic regression. Although its linear summation assumption is concise, it may not fully capture the interactions between variables, resulting in a slightly lower AUC (0.721) in the validation set compared to machine learning models that can capture nonlinear relationships.

Regarding the differences in the ranking of variable importance, different models have provided different results. For example, in multi factor logistic regression (nomogram), decision trees, random forests, and GBM model models, IIH is placed at the forefront; In the importance ranking of neural networks, TNM staging ranks first, followed by IIH. This difference mainly stems from the different internal mechanisms by which various models evaluate the importance of variables. Logistic regression and decision trees (based on Gini coefficient) provide global and average effect estimates. The importance calculation of neural networks is usually based on the accumulation of connection weights or observing output changes through perturbation of inputs, which may be more sensitive to the "hub" role of variables in complex interactive networks [40]. In this study, the neural network model may identify TNM staging as a key "background" factor that determines the size of the effects of other variables (such as IIH), and therefore assign it higher importance. Although the rankings are slightly different, all models unanimously agree that IIH, TNM staging, tumor location, and CEA are the core elements for predicting short-term prognosis, which indirectly confirms that the risk factors we have screened are robust and critical. It is worth to note that compared with tumor location, TNM stage and CEA level in the model, intraoperative hypothermia was the only key factor in the model with a high degree of intervention. This finding greatly enhances the clinical value of this study, because it means that by implementing active warming measures (e.g., use of warming blankets, warm fluid infusion, etc.), clinical teams can directly intervene in this risk factor, which is expected to significantly reduce the risk of poor short-term prognosis of patients and provide a clear and feasible entry point for improving perioperative management.

In summary, although multiple models are effective, caution should be exercised in clinical applications due to the instability of decision trees in the validation set. The nomogram, due to its intuitive and visual advantages, is convenient for clinical doctors to quickly conduct bedside assessments and has high practical value. Neural networks and gradient boosting machines, with their powerful nonlinear fitting capabilities, have shown potential in prediction accuracy and can be used as core algorithms for auxiliary decision support systems in the future, especially for integration into electronic medical record systems for real-time risk warning. However, this study also has certain limitations, the limitations of this study stem primarily from its retrospective study design, which resulted in a relatively limited number of variables that could be included in the analysis. First, retrospective studies rely on previous medical records, which may not have detailedly recorded all potential relevant factors and failed to collect the duration of patients' hypothermia, which may limit the ability to comprehensively assess the risk factors for short-term poor prognosis. Second, due to the lack of randomization and the collection of prospective data, it is impossible to completely exclude the influence of unmeasured confounding factors on the results, which may affect the accuracy and generalizability of the research results. Third, clinical validation uses consecutive samples from the same hospital, and its application to other populations or hospitals is still limited. Fourth, the study only observes the overall prognosis of patients and fails to specifically describe which specific complications are increased in risk for patients with IIH.

Conclusion

This study reveals the occurrence of intraoperative hypothermia in patients undergoing laparoscopic radical resection of colorectal cancer and it is an independent risk factor for poor short-term prognosis. Intraoperative hypothermia significantly increases the risk of poor short-term prognosis of patients. In addition, this study identified independent risk factors such as the tumor location in the rectum, TNM stage at III, and CEA ≥5 ng/mL. The nomogram prediction model constructed based on these factors demonstrated excellent predictive efficacy and clinical practicability in comparison with multiple models, which can help optimize perioperative management and improve the short-term prognosis of patients.

Disclosure of conflict of interest

None.

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