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ORIGINAL RESEARCH

Risk Factors and Predictive Model for Stress Hyperglycemia After Cardiac Surgery in Non-Diabetic Patients

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Objective: To create and verify a model that predicts the risk of stress hyperglycemia (SHG) in patients without diabetes after cardiac surgery.

Design: Retrospective analysis.

Methods: This retrospective analysis analyzed patients without diabetes post cardiac surgery at our hospital between June 2020 and December 2023. The 333 patients from June 2020 to June 2022 constituted the developmental sample and the 162 patients from July 2022 to December 2023 constituted the testing sample.

Results: Of 495 patients, 356 (71.9%) developed SHG. Multivariable analysis identified hyperlipidemia, coronary artery bypass grafting (CABG), hypertension, blood transfusion, body mass index (BMI) ≥28 kg/m², and hyperoxia during cardiopulmonary bypass ($PaO_2 \geq 300$mmHg) as significant factors influencing SHG in patients without diabetes after cardiac surgery. The goodness-of-fit test for the risk prediction model based on these factors showed $X^2 = 0.85$, $P = 0.588$. The area under the receiver operating characteristic curve (AUC) for the modeling group was 0.85, with a maximum Youden index of 0.579, an optimal cutoff value of 0.637, a sensitivity of 83.4%, and a specificity of 74.5%. For the external validation group, the AUC was 0.805, with a Youden index of 0.704, 82.6% sensitivity, and 87.8% specificity, and a diagnostic value of 0.839.

Conclusion: Hyperlipidemia, CABG, hypertension, blood transfusion, BMI ≥28 kg/m², and hyperoxia during CPB ($PaCO_2 \geq 300$mmHg) are significant risk factors for SHG in patients without diabetes following cardiac surgery. The model constructed based on these factors can effectively predict the risk of SHG, providing a basis for early intervention measures reduce the incidence of this condition.

Keywords: cardiac surgery, stress hyperglycemia, SHG, contributing factors, risk prediction model, nursing, R software

Introduction

Stress hyperglycemia (SHG) refers to a temporary increase in blood glucose levels in patients under high-stress conditions, such as major trauma, severe infection, or cardiovascular events, without a prior history of diabetes.[1,2] Stress hyperglycemia is characterized by increased blood glucose levels in individuals with no previous diagnosis of diabetes. It is identified when fasting glucose levels surpass 6.9 mmol/L or when random glucose levels are above 11.1 mmol/L. This condition is also referred to as hospital-associated hyperglycemia.[3] Cardiac surgery is a significant stressor for hospitalized patients without diabetes, often leading to SHG and other common postoperative complications, such as increased risk of infection, delayed wound healing, elevated risk of cardiovascular events, impaired kidney function, multiple organ dysfunction, and Prolonged hospitalization and higher mortality rate.[2,4] Studies have shown that the incidence of SHG in patients without diabetes after cardiac surgery is approximately 70%-75%.[5,6] With ongoing

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research, scholars have introduced differing perspectives, suggesting that stress hyperglycemia can lead to carbon monoxide production, which affects tissue blood circulation.[7,8] This disruption may result in metabolic imbalances, impair the protective function of the blood-brain barrier, and cause damage to various organs, increasing the risk of infection, multi-organ dysfunction, and even life-threatening complications. Studies indicate that stress-induced hyperglycemia is not a protective defense mechanism, but rather an adverse physiological response associated with higher mortality.[9] Additionally, researchers found that stress hyperglycemia in non-diabetic patients can be a predictor of future diabetes diagnosis.[10] Among non-diabetic patients who experienced stress hyperglycemia, 34% were diagnosed with diabetes during follow-up three months after discharge. Previous research examined the risk factors for SHG in patients without diabetes after cardiac surgery and used risk prediction models for patients with digestive tract malignancies and ICU patients.[11–14] This study provides a detailed analysis of stress-induced hyperglycemia (SHG) risk factors across different patient groups by comparing existing prediction models, including those for SHG risk in gastric cancer and ICU patients, as well as models for non-diabetic patients after cardiac surgery. The findings suggest that SHG risk in gastric cancer and ICU patients is more closely associated with severe stress responses, pharmacological treatments, and therapeutic protocols, whereas SHG risk in non-diabetic cardiac surgery patients is strongly linked to preoperative, intraoperative extracorporeal circulation, and postoperative physiological stress. In contrast to existing models that primarily focus on the analysis of SHG risk factors in non-diabetic cardiac surgery patients, this study's model integrates additional clinical factors and constructs a nomogram, offering a more precise risk prediction, particularly for non-diabetic patients. This enhances the clinical applicability and validity of the model. Therefore, developing a risk prediction model for SHG is crucial for the early identification and prevention of this condition in patients without diabetes following cardiac surgery. A nomogram visually presents the risk prediction model, predicting the probability of risk occurrence by calculating the total score of each independent risk factor. This study aimed to include risk factors for postoperative SHG to evaluate and establish a nomogram prediction model, provide an early warning for SHG risk in postoperative cardiac surgery patients, and offer a basis for clinical healthcare workers to accurately assess and formulate individualized preventive measures.

Methods

Study Design

This observational retrospective study aimed to evaluate the predictive factors of stress-induced hyperglycemia in non-diabetic patients after cardiovascular surgery.

Study Population

A retrospective collection of 495 patients treated at the First Affiliated Hospital of Bengbu Medical University between June 2020 and December 2023 was included in the study.

Setting

The 333 patients from June 2020 to June 2022 constituted the modeling group for internal validation, and the 162 patients from July 2022 to December 2023 constituted the validation group for external validation.

Study Endpoints

The occurrence of stress-induced hyperglycemia (SHG) after cardiac surgery was used as the outcome variable.

Ethical Committee Approval

All study participants were fully informed and provided signed informed consent. The study received ethical approval from the Medical Ethics Committee of The First Affiliated Hospital of Bengbu Medical University (Ethics Approval Number: 2024KY012) and was conducted in accordance with the Helsinki Declaration. Patient information was kept confidential throughout the study.

Inclusion and Exclusion Criteria

The inclusion criteria were:

1. Patients were divided into normal blood glucose and SHG groups based on blood glucose levels monitored for three days post-surgery.
2. Those with fasting blood glucose <7.0 mmol/L were placed in the normal blood glucose group, while those with fasting blood glucose ≥7.0 mmol/L were placed in the SHG group.
3. Patients who underwent valve surgery, coronary artery bypass surgery, or major cardiovascular surgery were included in the study.

The exclusion criteria were:

1. Diabetes
2. Pregnancy
3. Active infections preoperatively
4. Direct postoperative ICU transfer
5. Pancreatectomy.

Sample Size Calculation

Based on a meta-analysis literature review and expert consultation, 35 risk factors were screened, and the sample size was calculated using a formula that multiplies the number of variables by 5–10.[15] Considering an SHG incidence rate of 70%-75%and a 20% loss to follow-up rate, the required sample size was 313–583, and 495 cases were ultimately selected.[5,6]

Data Collection

General Information: Data were collected from the permanent electronic medical record system, including name, sex, age, smoking and alcohol consumption history, and medical history.(eg, hypertension, heart disease, and liver and kidney dysfunction). Physical and Physiological Indicators: Height and weight data were sourced from the medical record system to calculate BMI. Serum albumin and hemoglobin data were obtained from preoperative blood indicators to determine whether the patients had anemia or hypoproteinemia.[16] Surgical and Nutritional Indicators: Data were collected from medical records, including the type of surgery (heart valve surgery, coronary artery bypass grafting, major cardiac vascular surgery), duration of surgery, type of anesthesia, and anesthetic drugs used. Blood Glucose Indicators: Blood biochemical indicators were checked once or twice within three days postoperatively in cardiac surgery patients. Since patients did not receive fluid treatment in the morning, the blood glucose value in biochemical tests can be considered as fasting blood glucose.

Statistical Analysis

Data were entered and double-checked in Microsoft Excel. Analysis was conducted using SPSS 26.0, and R was used for nomogram creation. Qualitative data are presented as frequencies and percentages (%), and group comparisons were made using the chi-square test or Fisher's exact test. Univariable and multivariable logistic regression analyses were used to identify the risk factors for SHG. Variables with $P<0.05$ in the univariable analysis were included in the multivariable model, adjusting for confounding factors. Adjusted odds ratios (ORs) and 95% confidence intervals (95% CIs) were calculated. The final prediction model was a logistic regression model visualized using a nomogram. Receiver operating characteristic (ROC) curves were plotted and the area under the curve (AUC) was determined. The Hosmer-Lemeshow test was used to assess the model prediction ability and goodness of fit.

The Development Process of the Nomogram

Data Collection and Preprocessing

Initially, relevant data from non-diabetic patients following cardiac surgery is collected. These data typically include the patient's basic information (such as age, sex, weight, and BMI), medical history, type of surgery, and other clinical factors that may influence the occurrence of SHG (such as hypertension, hyperlipidemia, and intraoperative medication use). The data must be cleaned and standardized to ensure quality and consistency.

Risk Factor Selection

Statistical methods (such as univariable analysis) are used to identify potential variables that may be associated with SHG. This step typically involves analyzing the relationship between each variable and the occurrence of hyperglycemia, with factors showing a significant effect ($P<0.05$) being selected for further analysis.

Multivariable Analysis

Multivariable regression analysis (usually employing logistic regression models) is conducted to further assess the independent impact of each selected variable on the likelihood of SHG. The purpose of this step is to determine the weights or coefficients of each variable and verify which variables continue to have a significant impact after controlling for other factors.

Nomogram Construction

Based on the results of the regression analysis, a nomogram is constructed. The nomogram is a graphical tool where each relevant variable corresponds to a score. The scores are allocated based on the coefficients of each variable, and the sum of these scores is used to predict the patient's risk of developing SHG. These scores are then mapped to a risk value on the nomogram's scale.

Model Validation and Evaluation

The nomogram is subjected to internal validation using methods such as cross-validation and the Bootstrap method to assess its predictive accuracy and stability. Common evaluation metrics include the calibration curve and the receiver operating characteristic (ROC) curve, which confirm the model's applicability and generalizability to new samples.

Risk Threshold Setting

High Risk: When the model's risk score or predicted probability is high (eg, exceeding 70%), it typically indicates that the patient requires closer monitoring and may need additional preventive interventions or treatment.

Moderate Risk: For patients categorized as moderate risk (eg, 50%-70%), regular monitoring and appropriate preventive measures may be necessary.

Low Risk: Patients classified as low risk (below 50%) generally do not require extensive intervention but should still undergo routine monitoring.

Clinical Application

The final nomogram can be utilized as a clinical tool to help physicians quickly assess the risk of SHG in non-diabetic patients following surgery, providing a basis for personalized management and decision-making.

Example

Suppose that several risk factors for SHG were identified in a clinical study, including BMI≥28 kg/m², age, whether CABG was performed, hypertension, hyperlipidemia, and high oxygen conditions during cardiopulmonary bypass (CPB). After performing multivariable regression analysis, the following nomogram was developed:

BMI≥28 kg/m² = 80 points, BMI<28 kg/m² = 0 points; CABG = 49 points, no CABG = 0 points; Hyperlipidemia = 25 points, no hyperlipidemia = 0 points; Hypertension = 47 points, no hypertension = 0 points; Blood transfusion = 100 points, no blood transfusion = 0 points; High oxygen state during CPB = 50 points, no high oxygen state = 0 points.

For a patient with hyperlipidemia, hypertension, and having undergone CABG, their score would be:25 (hyperlipidemia) + 47 (hypertension) + 49 (CABG) = 121 points.According to the nomogram, this would correspond to an

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approximate risk of 60%. This example demonstrates how the nomogram can be used in clinical practice to quickly estimate the risk of SHG in a patient, facilitating more informed and personalized treatment decisions.

Application of the Risk Prediction Model Nomogram

Target Users

① Clinical Healthcare Providers: This includes doctors, nurses, and endocrinologists. The nomogram can assist professionals in making informed clinical decisions by applying a predictive model, enabling the creation of personalized treatment and care plans based on each patient's risk level.② Researchers: In medical and nursing research, nomograms can be used to assess patient risks and evaluate the effects of different clinical interventions on stress hyperglycemia (SHG).③ Patients and Families: Although primarily designed for healthcare professionals, the nomogram's simplicity and visual clarity make it useful for explaining postoperative blood sugar risks to patients and their families, helping to improve adherence and confidence.

Research Tools

(1) This study employed a self-designed questionnaire to gather clinical information from patients.(2) Questionnaire Setup: Drawing on evidence-based literature reviews of the influencing factors of SHG in patients without diabetes during hospitalization, discussions within the research team, expert consultations, and input from frontline cardiac surgery healthcare staff, a questionnaire was developed to investigate the risk factors associated with SHG. The design principles of the questionnaire included ensuring that the factors were quantifiable, easily obtainable, suitable as common clinical indicators, and specifically targeted to reflect the necessary evaluation content.(3) The questionnaire comprises the following main sections:①General Information: Includes the patient's name, gender, age, BMI, medical history, smoking and alcohol consumption history, among others.②Disease-Related Information: Covers details such as the type and duration of surgery, anesthesia type, specific anesthetic drugs administered, occurrence of blood transfusion, whether a second surgery was performed, various laboratory indicators, use of cardiopulmonary bypass during surgery, aortic clamping duration, preoperative and intraoperative medications, and preoperative and post-operative blood glucose levels.

Quality Control

(1) Data were entered jointly by two graduate students using Microsoft Excel. After completion, 10% of the patient records were randomly selected for reexamination to check for data discrepancies and ensure the accuracy of the entered data.
(2) This study strictly adhered to the inclusion and exclusion criteria for the selection of participants. The study design and implementation were completed under expert guidance, and all medical staff involved in the questionnaire design possessed extensive clinical experience.

Timing of Use

The nomogram can be used throughout the perioperative period, including preoperative, intraoperative, and post-operative stages: ① Preoperative Assessment: The nomogram can be used before surgery to assess each patient's baseline risk. By considering factors such as age, sex, and medical history (eg, hypertension and cardiovascular disease), healthcare providers can identify high-risk individuals for SHG and plan interventions in advance, such as preoperative blood sugar monitoring and medication adjustments. Intraoperative Management: During cardiac surgery, particularly when extracorporeal circulation is involved, fluctuations in blood glucose levels are common. The nomogram allows anesthesiologists and the nursing team to determine the frequency of monitoring and managing blood sugar levels in real-time based on predicted risks and to adjust insulin or other interventions to prevent SHG. Postoperative Management: The postoperative period is associated with a high risk of stress hyperglycemia. Using this nomogram, healthcare providers can tailor postoperative blood glucose management, including enhanced monitoring, medication adjustments, and nutritional support, based on the patient's recovery progress and risk scores.

Steps for Using the Nomogram

① Data Collection: First, healthcare providers need to gather the patients' personal and perioperative information, such as body mass index (BMI), medical history, type of surgery, and use of extracorporeal circulation.

② Nomogram Scoring: By inputting the relevant variables into the nomogram, healthcare providers can determine the corresponding scores for each variable. Individual scores were then summed to calculate the total score.

③ Risk Assessment: Based on the total score, the nomogram provides the corresponding probability of SHG. A higher total score indicates a greater risk of postoperative stress hyperglycemia.

④ Developing an Intervention Plan: Using the assessment results, the clinical team can develop a personalized perioperative management strategy for patients.

Diagnostic Value

1. Sensitivity: The ability of the model to correctly identify individuals who are diseased or at high risk.
2. Specificity: The ability of the model to correctly identify healthy individuals or those at low risk.
3. Predictive Accuracy: The degree to which the model correctly classifies individuals.
4. AUC (Area Under the Curve): A metric used to assess the classification ability of the model, where a value closer to 1 indicates stronger predictive performance.

Results

Univariable Analysis of General Information and Influencing Factors for SHG in Patients without Diabetes After Cardiac Surgery

In the modeling group, 235 patients (70.57%) developed SHG and 98 (29.43%) did not. Modeling group included 180 males (54%) and 153 females (46%). In the validation group, 121 patients (74.7%) developed SHG and 41 (25.3%) did not. Validation group included 101 males (62.3%) and 61 females (37.7%). Univariable analysis indicated significant differences between groups in terms of gender and type of heart valve surgery, coronary artery bypass grafting, BMI ≥28kg/m², abnormal liver function, hyperlipidemia, hypertension, elevated uric acid, ASA score ≥3, blood transfusion, aortic clamping time ≥110 minutes, use of norepinephrine during surgery, and hyperoxia status during cardiopulmonary by pass ($P<0.05$) as Table 1.

Table 1 Basic Information of SHG in Patients

Projects	SHG	Non-SHG	X^2 Test Statistic	p value
Age > 65 years			2.184	0.139
Non	148 (63%)	70 (71.4%)		
Yes	87 (37%)	28 (28.6%)		
Gender [% of cases (100%)]			8.346	0.004
Male	139 (40.9%)	41 (41.8%)		
Woman	96 (59.1%)	57 (58.2%)		
Type of operation				
Heart valve surgery			15.267	P<0.001
Non	117 (49.8%)	26 (26.5%)		
Yes	118 (50.2%)	72 (73.5%)		
Cardiac coronary artery bypass grafting			14.328	P<0.001
Non	150 (63.8%)	83 (84.7%)		
Yes	85 (36.2%)	15 (15.3%)		
Great vascular surgery of the heart			0.231	0.631
Non	228 (97%)	96 (98%)		
Yes	7 (3%)	2 (2%)		

(*Continued*)

Table 1 (Continued).

Projects	**SHG**	**Non-SHG**	**X^2 Test Statistic**	**p value**
Two kinds of operations			1.684	0.194
Non	213 (90.6%)	93 (94.9%)		
Yes	22 (9.4%)	5 (5.1%)		
Three kinds of operations			0.273	0.601
Non	232 (98.7%)	96 (98%)		
Yes	3 (1.3%)	2 (2%)		
BMI≥28kg/m^2			15.705	P<0.001
Non	124 (53.2%)	74 (75.5%)		
Yes	111 (46.8%)	24 (24.5%)		
Smoking history			0.028	0.868
Non	190 (80.9%)	80 (81.6%)		
Yes	45 (19.1%)	18 (18.4%)		
Drinking history			1.197	0.274
Non	205 (87.2%)	81 (82.7%)		
Yes	30 (12.8%)	17 (17.3%)		
History of cardiac surgery			0.013a	0.908
Non	212 (90.2%)	88 (89.8%)		
Yes	23 (9.8%)	10 (10.2%)		
Hyperlipidemia			7.113	0.008
Non	77 (32.8%)	40 (14.3%)		
Yes	158 (67.2%)	58 (85.7%)		
Renal failure			2.284	0.131
Non	233 (99.1%)	95 (96.9%)		
Yes	2 (0.9%)	3 (3.1%)		
Abnormal liver function			6.948	0.008
Non	202 (86%)	94 (95.9%)		
Yes	33 (14%)	4 (4.1%)		
CHF			0.785a	0.375
Non	181 (77%)	71 (72.4%)		
Yes	54 (23%)	27 (27.6%)		
Anemia			0.907	0.341
Non	173 (73.6%)	77 (78.6%)		
Yes	62 (26.4%)	21 (21.4%)		
Hypertension			15.705	P<0.001
Non	125 (53.2%)	75 (76.5%)		
Yes	110 (46.8%)	23 (23.5%)		
History of cardiogenic shock			0.217	0.641
Non	231 (98.3%)	97 (99%)		
Yes	4 (1.7%)	1 (1%)		
MI			0.890	0.346
Non	210 (89.4%)	84 (85.7%)		
Yes	25 (10.6%)	14 (14.3%)		
Leukocytosis			0.635	0.426
Non	209 (89%)	90 (91.8%)		
Yes	26 (11%)	8 (8.2%)		
Increased neutrophil numbers			0.352	0.553
Non	203 (86.4%)	87 (88.8%)		
Yes	32 (13.6%)	11 (11.2%)		

(*Continued*)

Table 1 (Continued).

Projects	SHG	Non-SHG	X^2 Test Statistic	p value
Elevated uric acid			51.973	P<0.001
Non	91 (38.3%)	79 (81.6%)		
Yes	146 (61.7%)	19 (18.4%)		
C-reactive protein > 5mg			0.111	0.74
Non	166 (70.6%)	71 (72.4%)		
Yes	69 (29.4%)	27 (27.6%)		
Creatinine increased > 200µmol			0.14	0.709
Non	223 (94.9%)	92 (93.9%)		
Yes	12 (5.1%)	6 (6.1%)		
Cardiac function grade ≥3			1.154	0.283
Non	79 (33.6%)	39 (39.8%)		
Yes	156 (66.4%)	59 (60.2%)		
ASA≥ Level 3			9.516a	0.002
Non	91 (38.7%)	56 (57.1%)		
Yes	144 (61.3%)	42 (42.9%)		
Valve surgery combined heart bypass surgery			2.681	0.102
Non	226 (96.2%)	90 (91.8%)		
Yes	9 (3.8%)	8 (8.2%)		
Aortic dissection			0.476	0.49
Non	221 (94%)	94 (95.9%)		
Yes	14 (6%)	4 (4.1%)		
Intraoperative blood loss > 1200mL			1.004a	0.316
Non	230 (97.9%)	94 (95.9%)		
Yes	5 (2.1%)	4 (4.1%)		
Aortic occlusion time ≥110min			5.124	0.024
Non	142 (60.4%)	72 (73.5%)		
Yes	93 (39.6%)	26 (26.5%)		
Blood transfusion			51.973	P<0.001
Non	90 (38.3%)	80 (81.6%)		
Yes	145 (61.7%)	18 (18.4%)		
Operation time > 5H			1.105	0.293
Non	77 (32.8%)	38 (38.8%)		
Yes	158 (67.2%)	60 (61.2%)		
Second operation			0.273	0.601
Non	232 (98.7%)	96 (98%)		
Yes	3 (1.3%)	2 (2%)		
Norepinephrine was used intraoperatively			4.462a	0.035
Non	139 (59.4%)	70 (71.4%)		
Yes	96 (40.9%)	28 (28.6%)		
Whether glucocorticoid drugs were used before surgery			0.020	0.887
Non	200 (85.1%)	84 (85.7%)		
Yes	35 (14.9%)	14 (14.3%)		
Cardiopulmonary bypass time > 3H			2.242	0.134
Non	158 (67.2%)	74 (75.5%)		
Yes	77 (32.8%)	24 (24.5%)		
CPB hyperoxic state			14.878	P<0.001
Non	72 (30.6%)	52 (53.1%)		
Yes	163 (69.4%)	46 (46.9%)		

(*Continued*)

Table 1 (Continued).

Projects	SHG	Non-SHG	X^2 Test Statistic	p value
Pulmonary disease			1.724	0.189
Non	216 (91.9%)	94 (95.9%)		
Yes	19 (8.1%)	4 (4.1%)		

Abbreviations: Non-SHG, Non-Stress Hyperglycemia; SHG, Stress Hyperglycemia; CHF, Congestive Heart-Failure.

Multivariable Analysis of Factors Influencing SHG in Patients without Diabetes After Cardiac Surgery

Variables with statistical significance ($P<0.05$) in univariable analysis were used as independent variables in multivariable logistic regression analysis, with SHG occurrence after cardiac surgery as the dependent variable. Results identified hyperlipidemia, coronary artery bypass grafting (CABG), hypertension, blood transfusion, BMI≥28 kg/m², and hyperoxia during cardiopulmonary bypass ($PaCO_2$≥300mmHg) as independent risk factors for SHG.[17] These factors were integrated to calculate the total score, which predicted the probability of SHG in patients without diabetes following cardiac surgery as Tables 2 and 3.

Developing a Nomogram to Predict Stress Hyperglycemia (SHG) Risk in Patients without Diabetes After Cardiac Surgery

Using logistic regression results, we constructed a risk prediction model by incorporating factors influencing SHG in patients without diabetes after cardiac surgery. The logistic regression equation: $-3.999 + 1.693 \times (\text{BMI}\geq 28\ \text{kg/m}^2) + 1.068 \times (\text{Preoperative hyperlipidemia}) + 0.909 \times (\text{Hypertension}) + 2.138 \times (\text{Blood transfusion}) + 0.928 \times (\text{Hyperoxia during CPB}) + 1.495 \times (\text{CABG})$ visual nomogram was drawn, where each factor corresponds to a specific score. The

Table 2 Variable Assignment

Variable Name	Assignment
Hyperlipidemia	Non=0 Yes=1
Coronary artery transplantation	Non=0 Yes=1
Hypertension	Non=0 Yes=1
Blood transfusion	Non=0 Yes=1
BMI	BMI≥28kg/m^2=0 BMI<28kg/m^2=1
Mean arterial partial pressure of oxygen	Mean arterial partial pressure of oxygen < 300mmhg=0 Mean arterial partial pressure of oxygen ≥300mmhg=1

Abbreviation: BMI, Body Mass Index.

Table 3 Multi-Factor Analysis of SHG Influencing Factors in Patients

	Regression Coefficient	SE	Wald X^2	P	OR Value	95% CI
Quantity	−3.999	0.919	18.936	P<0.001		
BMI≥28kg/m^2	1.693	0.364	21.607	P<0.001	5.435	[2.662–11.098]
Hyperlipidemia	1.068	0.517	4.274	0.039	2.91	[1.057–8.008]
Hypertension	0.909	0.346	6.92	0.009	2.483	[1.261–4.888]
Blood transfusion	2.138	0.371	33.207	P<0.001	8.484	[4.1–17.555]
Mean arterial partial pressure of oxygen	0.928	0.321	8.376	0.004	2.529	[1.349–4.741]
CABG	1.495	0.667	5.03	0.025	4.459	[1.208–16.465]

Abbreviation: CABG, Coronary Artery Bypass Grafting.

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total score, calculated by summing the scores from all factors, predicted the likelihood of SHG in patients without diabetes after cardiac surgery as Figures 1 and 2.

Model Development

The Hosmer-Lemeshow test indicated good model fit (χ^2=6.532, P=0.588). The sensitivity and specificity of the model were assessed using the ROC curve, with the optimal diagnostic threshold determined by the maximum Youden index, which achieved an AUC of 0.85, a maximum Youden index of 0.579, and an optimal cutoff of 0.637, resulting in 83.4% sensitivity and 74.5% specificity as Figure 3.

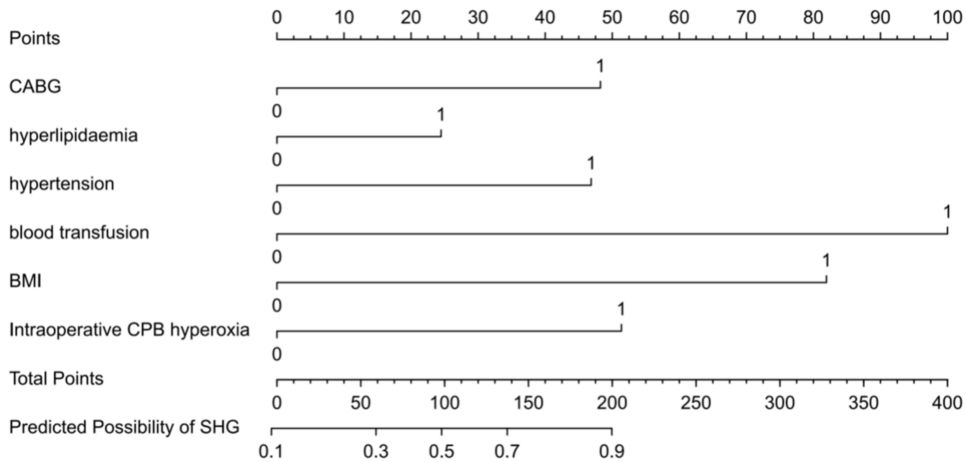

Figure 1 The construction of a nomogram for predicting the risk of stress hyperglycemia in patients.

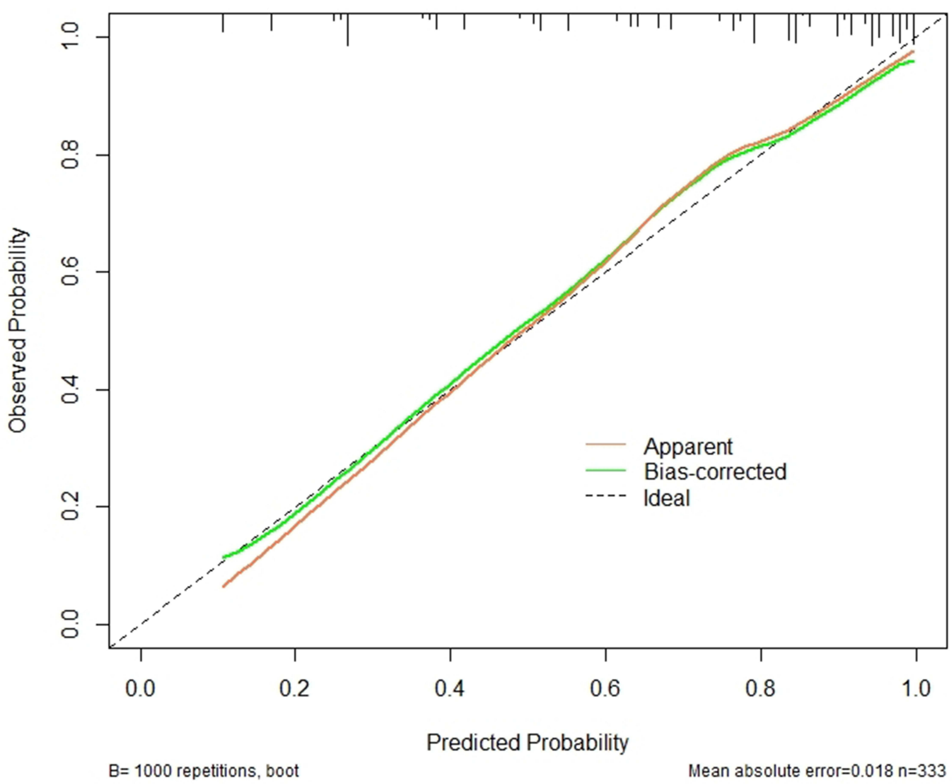

Figure 2 Calibration of risk factors for SHG in patients.

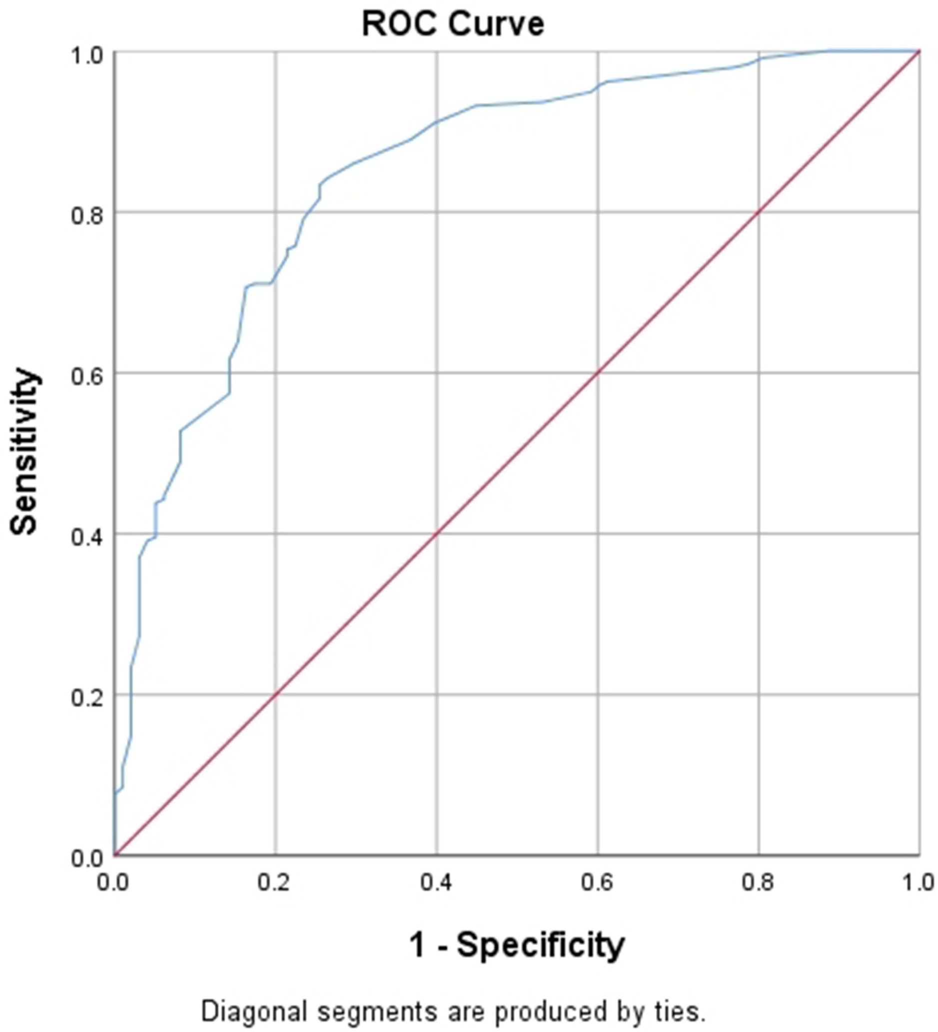

Figure 3 ROC curve of the modeling group.

Model Validation

In the external validation group, the AUC was 0.805 with a maximum Youden index of 0.704, indicating 82.6% sensitivity and 87.8% specificity, yielding a diagnostic value of 0.839 as Figure 4.

Model Performance and Comparison with Existing SHG Prediction Models

In this study, the performance of the developed model was evaluated using the area under the receiver operating characteristic curve (AUC) and its 95% confidence interval (CI). The AUC value of the proposed model was compared with that of existing stress-induced hyperglycemia (SHG) prediction models, thereby further validating the effectiveness of this model. Specifically, the calibrated AUC of our model was 0.85 (95% CI: 0.804–0.896), demonstrating a high predictive ability. When compared with existing SHG prediction models, such as those for gastric cancer patients (AUC: 0.752, 95% CI: 0.711–0.793) and ICU patients (AUC: 0.776, 95% CI: 0.669–0.883), the predictive accuracy of our model was notably superior. This comparison enhances the clinical applicability and predictive effectiveness of our model, providing a more precise tool for the early identification and intervention of high-risk patients.

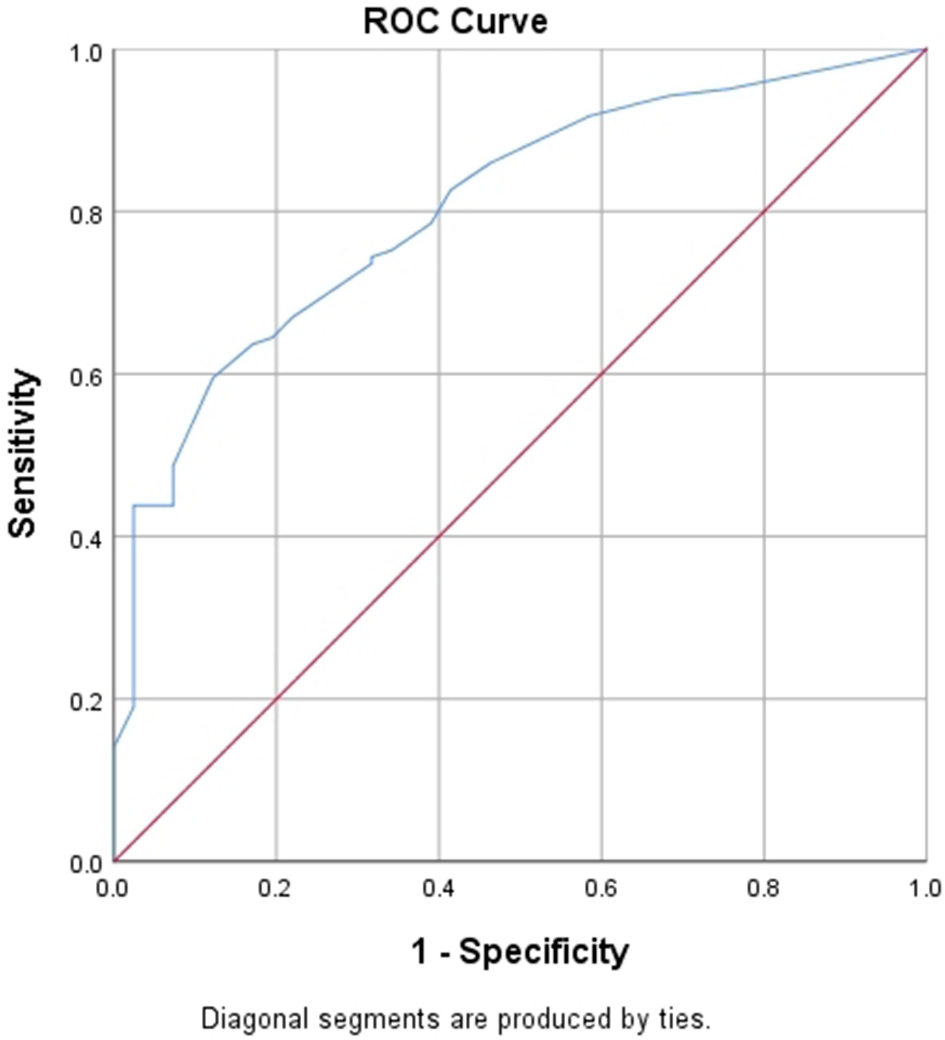

Figure 4 Displays the ROC curve for the validation group.

Discussion

In this study of 495 patients who underwent cardiac surgery, 356 developed SHG, resulting in an incidence rate of 71.9%, which was slightly lower than the 75% reported by Grocott HP.[18] This lower incidence may be attributed to the enhanced preventive measures against SHG implemented by healthcare personnel in recent years. Postoperative hyperglycemia is common among cardiac surgery patients, and prolonged peak blood glucose levels can adversely affect prognosis. Previous studies have explored risk factors for SHG in patients without diabetes following surgery.[11,12] However, variations in study factors necessitate comprehensive data analysis to reduce bias. The dynamic nature of SHG reflects its ever-changing process, which is an evolving and dynamic process. Identifying preoperative and intraoperative risk factors for SHG and performing individualized predictions can help early and accurately identify high-risk individuals during surgery, thereby improving early warning effectiveness. This study established a nomogram based on hyperlipidemia, coronary artery bypass grafting (CABG), hypertension, blood transfusion, BMI ≥28 kg/m², and hyperoxia during cardiopulmonary bypass (CPB).

Healthcare personnel can calculate the risk of SHG in patients without diabetes after cardiac surgery based on these factors. This model offers higher predictive accuracy and a more convenient calculation method, enabling frontline healthcare workers to quickly identify high-risk individuals and implement targeted preventive measures. In this study, among 162 patients, 121 cases of SHG were actually observed, and the model predicted 130 cases of postoperative SHG.

There were 41 cases in which SHG did not occur, and the model predicted 36 non-SHG cases. In the external validation group, the AUC was 0.805 with 82.6% sensitivity and 87.8% specificity at a maximum Youden index of 0.704, indicating a diagnostic value of 0.839. This demonstrates that the model's prediction of SHG probability closely matches the actual occurrence, providing high accuracy.

The results of this study indicate that preoperative hyperlipidemia is a risk factor for SHG. High blood sugar levels may lead to low-density lipoprotein (LDL) oxidation. After being engulfed by macrophages, glycated LDL is transformed into foam cells that are deposited in the vascular wall, accelerating the development of atherosclerosis and cerebrovascular complications, thereby affecting patient outcomes.[19] International studies have shown that dyslipidemia affects the body's oxidative stress capacity, impairing β-cell function, reducing insulin secretion, and raising blood glucose levels. Xie Huihui and Wang Yu also confirmed that dyslipidemia is a contributing factor to SHG.[20,21] Blood transfusion is an independent risk factor for SHG after cardiac surgery, potentially due to the promotion of the systemic inflammatory response syndrome, which is closely associated with a hypercoagulable state.[22] During blood transfusions, particularly large-volume transfusions, inflammatory responses can activate the release of stress hormones, leading to elevated blood glucose levels. Red blood cell suspensions stored for longer periods accumulate metabolic products (such as potassium ions and lactate) and cell debris, which can trigger immune and inflammatory responses and lead to SHG. Blood transfusion can also cause the release of cytokines (eg, TNF-α, IL-1, and IL-6) that promote insulin resistance and gluconeogenesis, resulting in elevated blood glucose levels.[23] Patients undergoing coronary artery bypass grafting (CABG) are at high risk of developing SHG. Studies show that patients undergoing CABG with extracorporeal circulation experience a higher incidence of hyperglycemia.[10] CABG significantly affects blood glucose levels due to factors such as heparin anticoagulation, blood dilution, mild hypothermia, and nonpulsatile flow during surgery. These factors collectively lead to an increased secretion of hyperglycemic hormones, such as glucagon and growth hormones, while decreasing insulin secretion, thus increasing blood glucose levels. Additionally, CABG combined with extracorporeal circulation stimulates the body's stress response, resulting in a series of changes in neuroendocrine function, organ function, and metabolism, primarily manifesting as insulin resistance and decreased insulin sensitivity, along with the release of numerous cytokines and inflammatory mediators.[7,24] A history of hypertension was an independent risk factor for postoperative SHG, which is consistent with previous research.[25,26] Wang et al found that hypertension was an independent risk factor for SHG based on pre-admission systolic and diastolic blood pressure data.[27] Hao Zhihua observed that a higher baseline blood pressure was associated with more significant changes in fasting blood glucose levels and an increased risk of glucose elevation.[28] Literature from the United States reports that abnormal blood pressure in women is an independent risk factor for hyperglycemia.[29] A prospective study indicated that good blood pressure control could reduce the incidence of hyperglycemia.[30] Poor blood pressure control significantly increases the risk of hyperglycemia in patients without diabetes.[31] This study shows that a BMI of ≥28 kg/m² increases the risk of SHG in patients without diabetes after cardiac surgery, consistent with previous finding.[13] Research indicates that obesity-induced chronic inflammation plays a significant role in the development of SHG. As body weight increases, fat cells expand, leading to insufficient vascular supply and the release of free fatty acids, reactive oxygen species, and pro-inflammatory factors such as IL-6, IL-1, TNF-α, adiponectin, and leptin from adipose tissue.[32] Chronic overproduction of free fatty acids and their excessive accumulation in non-adipose tissues, such as the skeletal muscle, heart, and liver, leads to ectopic lipid deposition and lipotoxicity. Ectopic fat induces inflammation and activates apoptosis, which is a key factor in SHG.[33] The results of this study revealed that a high-oxygen state during extracorporeal circulation is an independent factor influencing SHG levels in patients without diabetes after cardiac surgery. This may be due to the strong stimulation caused by the high oxygen state combined with factors such as anesthesia, trauma, and hypothermia during surgery, which enhances the oxidative stress response and induces hyperglycemia.[6] Furthermore, a high oxygen state during extracorporeal circulation, along with postoperative factors such as hypoxia, pain stimulation, CO_2 retention, and intubation, can increase the release of catabolic hormones such as glucocorticoids and glucagon, leading to insulin resistance and elevated blood glucose levels.[34]

The nomogram provides personalized risk assessment for SHG by quantifying each risk factor. This enables healthcare providers to perform quantitative analyses of each patient's risk and develop individualized care plans.

Using the nomogram prediction model, providers can plan interventions in advance based on a patient's risk level. Targeted prevention and intervention measures should be developed and implemented in advance for high-risk patients.

Optimizing lipid control during the perioperative period, including the use of medications (eg, statins) to manage lipid levels, can reduce the risk of postoperative complications. Proper lipid management improves cardiac surgical outcomes and lowers the incidence of postoperative SHG. Dietary and exercise interventions, such as following a low-fat diet and engaging in moderate exercise preoperatively, help improve lipid levels and enhance metabolic health. Healthcare providers should avoid excessive blood transfusions and use fresher red blood cells to minimize red cell function decline and metabolic product accumulation due to prolonged storage, thereby reducing stress responses. Effective preoperative and intraoperative blood pressure management in hypertensive nondiabetic cardiac patients is crucial, including the optimization of blood pressure control and timely adjustment of antihypertensive medications and treatment plans. Additionally, measures to reduce stress responses during surgery, such as controlling the depth of anesthesia and using stress inhibitors, can help prevent postoperative SHG. Preoperative weight management in obese patients should include a comprehensive assessment of the obesity level, metabolic status, and cardiopulmonary function to create individualized care and treatment plans. During surgery, real-time blood glucose monitoring should be conducted to maintain blood glucose within normal ranges, adjust the insulin dosage based on the monitoring results, and use appropriate anesthesia and analgesia methods to minimize blood glucose fluctuations due to surgical stress. Postoperatively, individualized nutritional support should be provided to avoid a high-sugar diet. High oxygen levels can increase oxidative stress and inflammation, leading to stress hyperglycemia. Avoid excessive oxygen concentrations during extracorporeal circulation, maintain oxygen partial pressure within a reasonable range, and personalize oxygen flow based on patient condition, age, type of surgery, and duration of extracorporeal circulation. Appropriate supplementation with antioxidants (eg, vitamin C, vitamin E, and N-acetylcysteine) can help reduce oxidative stress during extracorporeal circulation, thereby decreasing the occurrence of stress hyperglycemia. During rewarming after extracorporeal circulation, rapid or excessive warming is avoided to prevent an excessive metabolic load, thus reducing postoperative stress responses and hyperglycemia. Prolonged extracorporeal circulation increases inflammation and oxidative stress, potentially leading to postoperative stress hyperglycemia. Optimizing surgical procedures to shorten the duration of extracorporeal circulation and minimize metabolic load is essential. Reducing downtime during extracorporeal circulation and maintaining stable circulation can help prevent stress responses caused by repeated start-stop cycles, provide a scientific basis for nursing practice, help nursing teams develop care pathways based on risk levels, and optimize care processes. The nomogram model not only aids clinical nursing decisions, but also supports nursing research using data. Through the application of this model, researchers have identified new risk factors, validated the effectiveness of nursing interventions, and enhanced evidence-based nursing practices. Future research integrating multicenter data can continuously refine and improve the prediction models and offer more precise references for future nursing studies. The intuitive and easy-to-understand nature of the nomogram helps healthcare providers communicate patient risk status and care plans more clearly to patients and their families, thereby increasing patient adherence and improving postoperative recovery. Multidisciplinary collaboration, including nursing, anesthesia, and endocrinology, can enhance comprehensive skills among healthcare providers, foster teamwork in nursing practice, and improve care quality.

Improved SHG Prediction for Non-Diabetic Cardiac Surgery Patients

Firstly, existing stress-induced hyperglycemia (SHG) prediction models, such as those developed for gastric cancer and ICU patients, have been widely applied to specific clinical populations. However, these models primarily focus on patients with a history of diabetes or factors related to particular diseases, and they have not been extensively studied in the context of non-diabetic patients following cardiac surgery. Therefore, there are limitations in the applicability of these models to non-diabetic patients.

The model proposed in this study addresses this gap by incorporating multiple physiological stress factors during the preoperative, intraoperative, and postoperative periods, specifically tailored for non-diabetic patients. Compared to SHG prediction models for gastric cancer and ICU patients, our model not only retains traditional risk factors such as BMI, age, and history of hyperglycemia but also includes more detailed variables, such as oxidative stress during extracorporeal circulation and blood glucose fluctuations during postoperative recovery, thereby improving SHG prediction in non-diabetic patients. Furthermore, when comparing the AUC values of our model with existing models, the results show that our model's calibrated AUC is 0.85 (95% CI: 0.804–0.896), which represents a significant improvement over the AUCs for gastric cancer patients (0.752, 95% CI: 0.711–0.793) and ICU patients (0.776, 95% CI: 0.669–0.883). This result not only confirms the superior accuracy of our model but also demonstrates its broader clinical applicability, particularly in the context of non-diabetic patients following cardiac surgery. Through this comparison with existing SHG prediction models, the innovation and clinical value of our model are clearly highlighted. The model's precision and broad applicability provide clinicians with a more reliable tool for early identification of high-risk patients, thereby facilitating more effective postoperative interventions and treatments, ultimately offering stronger support for patient recovery.

Limitations

Personalized Risk Assessment: The nomogram for nursing intervention decision-making provides a personalized risk assessment for stress hyperglycemia (SHG) by quantifying various risk factors such as hyperlipidemia, coronary artery bypass grafting (CABG), hypertension, blood transfusion, BMI ≥28 kg/m², and high oxygen states during extracorporeal circulation. This allows healthcare providers to perform detailed risk analysis for each patient and develop individualized care plans. Using the nomogram prediction model, providers can plan interventions based on the patient's risk level. Scientific Basis for Nursing: The risk prediction model offers a scientific foundation for nursing practice, helping nursing teams establish care pathways based on risk levels and optimize care processes. Advancing Evidence-Based Practice: The application of the model enables nursing researchers to identify new risk factors, validate the effectiveness of nursing interventions, and enhance evidence-based nursing practice. Future research incorporating multicenter data can continuously refine and improve the prediction models and provide more precise references for future nursing studies. Promoting Interdisciplinary Collaboration: The development of a prediction model requires interdisciplinary collaboration involving nursing, anesthesia, endocrinology, and other fields. However, this study has some limitations, such as the use of data from a single hospital, which may introduce bias. Future research could expand to multicenter and larger-sample studies to improve the reliability of the results and provide better references for the early identification of high-risk groups for SHG after cardiac surgery.

Conclusions

The study identified Hyperlipidemia, CABG, hypertension, blood transfusion, BMI ≥28 kg/m², and hyperoxia during CPB were factors influencing SHG levels in patients without diabetes after cardiac surgery. The developed risk prediction model and nomogram will enable clinical personnel to effectively identify high-risk patients and implement timely preventive measures to reduce the incidence of SHG in non-diabetic cardiac surgery patients.

Abbreviations

BMI, Body Mass Index; CHF, Congestive Heart-Failure; CPB, Cardiopulmonary Bypass; CABG, Coronary Artery Bypass Grafting.

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