

A Prediction Model for In-Hospital Sternal Wound Complications After Aortic Dissection Surgery Based on Rewarming Time, Drainage Output, and Hemoglobin: A Retrospective Study

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Research Article

Keywords: Aortic Dissection, Sternal Wound Complications, Rewarming Time, Chest Tube Drainage, Anemia

Posted Date: October 11th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10540830/v1>

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Additional Declarations: No competing interests reported.

Abstract

Background

Currently, early and simple tools for assessing the risk of in-hospital sternal wound complications (SWC) following aortic dissection surgery remain lacking. This study aimed to develop and internally validate a prediction model based on early postoperative objective indicators.

Methods

Between January 2020 and December 2023, we consecutively enrolled patients with Stanford type A aortic dissection who met the inclusion criteria and underwent surgical treatment at our institution, following predefined exclusion criteria. A total of 243 patients were finally included, of whom 58 (23.9%) developed in-hospital SWC. Variables with $P < 0.1$ in univariate analysis were screened for collinearity and clinical relevance before entry into a multivariable logistic regression model using the Enter method. A nomogram was constructed based on the multivariable analysis results. The model's performance was evaluated via bootstrap internal validation (1000 resamples) in terms of discrimination (AUC), calibration, and clinical utility (DCA). A simplified scoring system was derived as an exploratory analysis.

Results

Multivariable logistic regression identified three independent predictors of in-hospital SWC: rewarming time (OR = 0.983 per minute, 95% CI: 0.970–0.996, $P = 0.012$), postoperative day 2 drainage output (OR = 1.22 per 100 mL, 95% CI: 1.10–1.35, $P = 0.002$), and postoperative day 1 hemoglobin (OR = 0.976 per g/L, 95% CI: 0.954–0.998, $P = 0.035$), all three of which were incorporated into the final nomogram. The constructed nomogram demonstrated moderate discriminative ability (AUC = 0.702, 95% CI: 0.630–0.775) and good calibration (calibration intercept = -0.115, slope = 0.888, Brier score = 0.170). The simplified scoring system showed an AUC of 0.699 (95% CI: 0.635–0.763). When patients were stratified into low- (0 points), intermediate- (1–2 points), and high-risk (3 points) groups, the event rates were 6.7%, 21.7%, and 38.6%, respectively, showing a significant increasing trend (P for trend = 0.004).

Conclusion

This study identified rewarming time, postoperative day 2 drainage output, and postoperative day 1 hemoglobin as independent predictors of in-hospital SWC after aortic dissection. The nomogram incorporating these three variables demonstrated moderate discriminative ability and good calibration upon internal validation, supporting its potential utility as an internally validated exploratory model for early risk stratification. The simplified scoring system derived from the model showed modest

performance as an exploratory tool and requires prospective external validation before clinical application.

Introduction

Stanford type A aortic dissection is an acute and rapidly progressive cardiovascular emergency associated with extremely high mortality if left untreated. Surgical intervention remains the most critical life-saving approach [1, 2]. Despite substantial improvements in surgical techniques and perioperative management that have significantly enhanced short-term survival, postoperative complications remain a major obstacle to patient recovery. Among these, sternal wound complications (SWC) represent a spectrum of postoperative wound issues with varying severity, typically including sternal dehiscence, wound healing failure, wound exudation/fat liquefaction, and deep sternal infection/mediastinitis, with possible overlap among different types. SWC has drawn increasing attention due to its relatively high incidence and potentially serious consequences. Taking the most severe form, deep sternal wound infection (DSWI), as an example, studies have shown that it can prolong hospital stay by more than twofold (34.4 days vs. 16.5 days) and increase healthcare costs by nearly threefold [3], while also significantly raising the risk of reoperation for debridement and nosocomial infection. Therefore, early identification of patients at high risk for SWC after aortic dissection surgery has become a pressing clinical priority.

However, there is currently a lack of early warning tools specifically designed for SWC after aortic dissection surgery. Existing risk assessment tools for cardiac surgery are predominantly based on preoperative factors, such as age, urgent status, left ventricular dysfunction, and history of reoperation [4], and fail to adequately account for the impact of intraoperative stress and postoperative dynamic pathophysiological changes on SWC. Accumulating evidence has shown that factors including cardiopulmonary bypass time, intraoperative anemia, and postoperative C-reactive protein levels are closely associated with the development of DSWI [5], and elevated postoperative oxidative stress levels have also been identified as an independent risk factor for postoperative complications [6]. However, these dynamic indicators are often overlooked in current risk stratification systems.

At the same time, the current approach to SWC detection remains largely passive—relying on visible local wound changes such as delayed healing, dehiscence, or persistent exudation—which often leads to delayed diagnosis and missed opportunities for early intervention. Early identification of postoperative complications faces multiple challenges, including the diversity of complications, the non-specific nature of clinical manifestations, and the lack of sensitive and specific early diagnostic biomarkers [7]. Taking DSWI as an example, although C-reactive protein (CRP) levels on postoperative days 10 and 14 are significantly associated with infection, its predictive value in the early postoperative period remains limited, making ultra-early warning difficult to achieve [8]. Studies have confirmed that delayed debridement or delayed flap reconstruction in the management of DSWI is significantly associated with higher mortality and prolonged hospital stay [9], further underscoring the critical role of early recognition and timely intervention in improving outcomes.

In recent years, several studies have attempted to develop risk prediction models for SWC-related complications after cardiac surgery. For instance, Kalisnik et al. [10] applied machine learning algorithms to predict DSWI in patients undergoing coronary artery bypass grafting (CABG), achieving good discriminative performance (AUC = 0.851). However, existing models are largely confined to specific surgical types (e.g., CABG), rely on preoperative static variables, and focus primarily on DSWI as a single outcome, with a notable lack of simple prediction tools based on early postoperative dynamic objective indicators for the full spectrum of SWC after aortic dissection. To address this gap, the present study aimed to develop and internally validate a SWC risk prediction model based on early postoperative objective indicators, and to simplify it into a bedside scoring system, thereby enabling early risk stratification and guiding precision prevention in clinical practice.

Materials and Methods

Study Design and Participants

This was a single-center retrospective cohort study conducted at the Department of Cardiothoracic and Vascular Surgery, the First Affiliated Hospital of Hengyang Medical School, University of South China (Hengyang, China). The study protocol was approved by the hospital's Ethics Review Committee (approval number: 2024LL0410001), and the requirement for informed consent was waived due to the retrospective nature of the study. Data were extracted from the hospital's electronic medical record system.

We consecutively enrolled patients with Stanford type A aortic dissection who underwent surgical treatment at our institution between January 2020 and December 2023. Inclusion criteria were: (1) preoperative diagnosis of Stanford type A aortic dissection confirmed by CT angiography; and (2) receipt of a standardized surgical treatment protocol involving the aortic root, ascending aorta, and/or aortic arch (including but not limited to the Bentall procedure, hemiarch/total arch replacement, Sun's procedure, and various combined techniques). Exclusion criteria were: (1) preoperative active infection; (2) missing key early postoperative laboratory or clinical variables; or (3) death within 24 hours after surgery. All surgeries were performed by a single dedicated surgical team using standardized perioperative protocols throughout the study period.

A total of 295 patients were initially screened. Of these, 52 were excluded: 18 due to preoperative active infection, 22 due to missing key postoperative variables, and 12 due to death within 24 hours after surgery. The final analytic cohort comprised 243 patients with complete data for all variables of interest.

Surgical Procedure and Perioperative Management

All surgeries were performed by a single dedicated surgical team using standardized perioperative protocols, which were applied uniformly to all patients.

During cardiopulmonary bypass (CPB), rewarming was conducted using a water bath heat exchanger at a controlled rate of $\leq 0.5^{\circ}\text{C}/\text{min}$. The temperature gradient between the water bath and nasopharyngeal temperature was maintained at $< 5^{\circ}\text{C}$, and the gradient between nasopharyngeal and rectal temperature was kept $< 3^{\circ}\text{C}$. CPB was terminated when the nasopharyngeal temperature exceeded 36.5°C and the rectal temperature exceeded 36°C . All patients were rewarmed to normothermia ($\geq 37^{\circ}\text{C}$) before leaving the operating room. Standard perioperative protocols were also followed for antibiotic prophylaxis, glycemic control, and blood transfusion.

Outcome Definition and Data Collection

The primary outcome of this study was defined as in-hospital sternal wound complications (SWC), which encompassed the following conditions occurring during the postoperative hospitalization: (1) sternal dehiscence confirmed by physical examination or imaging (chest CT or ultrasound), indicating failure of both soft tissue and bone healing; (2) wound healing failure or wound dehiscence requiring debridement and primary suture, indicating soft tissue healing failure without bone involvement; or (3) persistent wound exudation or fat liquefaction requiring additional dressing changes or bedside debridement, without evidence of wound disruption.

SWC was identified based on postoperative bedside wound assessment, independently evaluated by at least two attending physicians according to visual inspection, primarily based on local wound characteristics (exudate properties, healing status, degree of dehiscence, sternal stability) and the required intervention, regardless of whether infection was present. For patients who met criteria for more than one SWC category, a hierarchical classification based on the most severe clinical manifestation was applied (sternal dehiscence > wound healing failure/dehiscence > persistent wound exudation/fat liquefaction), and each patient was counted in only one SWC category. Of note, some SWC patients (particularly those with sternal dehiscence) may have developed concomitant infection during the disease course; however, the SWC classification was based on local wound characteristics and the required intervention, and infection markers were not used as grouping criteria. Superficial incisional infection without wound healing failure, dehiscence, or sternal involvement was not counted as SWC.

All outcome events were adjudicated by at least two attending physicians, with consensus reached through discussion in cases of disagreement. No routine post-discharge surveillance was conducted; all events were identified during the index hospitalization.

Statistical Analysis

All analyses were performed using SPSS and R. Statistical significance was set at a two-sided P value < 0.05 . The analysis followed a staged approach as outlined in Fig. 1.

Data Preparation and Descriptive Analysis

Descriptive statistics were used to summarize the baseline characteristics of the cohort. Continuous variables were first tested for normality using the Shapiro–Wilk test and for homogeneity of variance using Levene’s test. Variables following a normal distribution ($P > 0.05$) were presented as mean $\pm$ standard deviation, while those with a non-normal distribution ($P \leq 0.05$) were presented as median (interquartile range). Categorical variables were presented as frequency (percentage).

For univariate comparisons between the SWC and non-SWC groups, continuous variables were analyzed using the independent samples t-test when normally distributed with homogeneous variances; otherwise, the Mann–Whitney U test was applied. Categorical variables were compared using the Chi-square test, or Fisher’s exact test when any expected cell frequency was less than 5.

All potential predictor variables were examined in univariate analysis. Variables with a P-value < 0.1 in the univariate analysis were retained as candidates. These candidate variables were then assessed for collinearity using Spearman’s correlation analysis and further screened based on clinical mechanistic judgment to avoid the influence of multicollinearity on multivariable regression results. In addition, the number of variables entered into the multivariable model was controlled based on the number of SWC events ($n = 58$) to ensure a sufficient events per variable (EPV). After the above screening, the final set of variables was entered into the subsequent multivariable logistic regression model.

Predictor Screening and Model Construction

After the screening procedure described above, the selected variables were entered into a binary logistic regression model using the Enter method to estimate independent associations with SWC. Odds ratios (ORs) with 95% confidence intervals (CIs) were calculated. Variables with $P < 0.05$ in the multivariable analysis were retained as independent predictors, and a nomogram was constructed based on these predictors to visualize individual SWC risk.

Internal Validation and Model Performance

The model’s performance was evaluated through internal validation using 1000 bootstrap resamples. Discrimination was assessed by the area under the receiver operating characteristic curve (AUC) with 95% CI. Calibration was evaluated using a calibration plot and quantified by the calibration intercept, calibration slope, Brier score, and mean absolute error (MAE). Clinical utility was assessed by decision curve analysis (DCA).

Development of the Simplified Scoring System

To provide an exploratory simplified representation of the nomogram, the nomogram prediction model was converted into a simplified risk scoring system. The optimal cut-off values for the continuous predictors were determined by maximizing Youden's index. Variables were dichotomized at these cut-offs (abnormal = 1 point, normal = 0 points), yielding a total score ranging from 0 to 3. Patients were

stratified into low-risk (0 points), intermediate-risk (1–2 points), and high-risk (3 points) groups. The Cochran–Armitage trend test was used to assess the trend of increasing event rates across groups, and the relative risk (RR) with 95% CI was calculated for each risk group compared with the low-risk group. The discriminative ability of the simplified scoring system was assessed by the area under the ROC curve (AUC).

Results

Patient Baseline Characteristics and Univariate Analysis Results

A total of 295 patients who underwent surgical treatment for Stanford type A aortic dissection were initially screened. After applying the predefined inclusion and exclusion criteria, 52 patients were excluded, and 243 patients were finally included in this study. Based on the occurrence of sternal wound complications (SWC), they were divided into two groups: a non-SWC group ($n = 185$) and an SWC group ($n = 58$), yielding an incidence of 23.9%. Clinical data from the preoperative, intraoperative, and postoperative periods were compared between the two groups using univariate analysis, with the results summarized in Table 1.

Overall, the majority of baseline characteristics showed no statistically significant differences between the two groups. Demographic profiles, including sex and age, as well as the prevalence of common comorbidities such as hypertension, diabetes, previous surgery history, and smoking history, were comparable between groups (all $P > 0.05$). Similarly, preoperative laboratory indices—including hemoglobin, total protein, albumin, cholesterol, creatinine clearance rate, and cardiac ejection fraction—showed no significant intergroup differences (all $P > 0.05$).

However, univariate analysis identified several factors associated with SWC. Among intraoperative indicators, rewarming time was shorter in the SWC group than in the non-SWC group, with borderline significance (79 [63.75, 92.25] min vs. 85 [69.5, 100.5] min, $P = 0.050$). Early postoperative observations revealed that postoperative day 2 drainage output was significantly higher in the SWC group (395 [198.75, 617.5] mL/day vs. 250 [137.5, 467.5] mL/day, $P = 0.006$). Postoperative day 1 hemoglobin was significantly lower in the SWC group (99 [89, 107] g/L vs. 101 [92.5, 114] g/L, $P = 0.043$). Postoperative day 1 lactate was also lower in the SWC group (2.1 [1.475, 3.2] mmol/L vs. 2.7 [1.8, 3.9] mmol/L, $P = 0.043$). Postoperative day 2 hemoglobin showed a borderline difference between groups (92.5 [85, 101] g/L vs. 98 [88, 108] g/L, $P = 0.050$). All other daily postoperative measures—including drainage output, hemoglobin, lactate, total protein, creatinine clearance rate, and blood glucose control—showed no statistically significant differences between the two groups (all $P > 0.05$).

Table 1

Comparison of Baseline Characteristics and Univariate Analysis Between the SWC and Non-SWC Groups. Continuous variables are presented as mean $\pm$ SD or median (IQR), and compared using the independent samples t-test or Mann-Whitney U test, as appropriate. Categorical variables are presented as n (%) and compared using the Chi-square test. All variables had complete data in the final analytic cohort (n = 243). Bold text indicates P < 0.05.

Preoperative Data:	Non-SWC group (n = 185)	SWC group (n = 58)	t/z/χ^2	P value
Sex (male)	134(72.4%)	44(75.9%)	0.265	0.607
Age (years)	53(45.5,63)	55(45.75,60.25)	-0.074	0.941
Height (m)	1.65(1.59,1.70)	1.68(1.62,1.72)	-1.782	0.075
Weight (kg)	65(57,75)	69(60,83.5)	-1.485	0.138
BMI (kg/m ²)	23.87(21.36,27.47)	25.50(21.25,27.90)	-0.984	0.325
Body surface area (m ²)	1.81 $\pm$ 0.25	1.88 $\pm$ 0.22	-1.791	0.075
Hypertension (yes)	102(55.1%)	28(48.3%)	0.835	0.361
Diabetes mellitus (yes)	4(2.1%)	1(1.7%)	0.042	0.838
Previous surgery history (yes)	54(29.2%)	13(22.4%)	2.956	0.086
Smoking history (yes)	31(16.8%)	10(17.2%)	0.007	0.931
Preoperative hemoglobin (g/L)	129(119,140)	124(109.75,141.25)	-1.715	0.086
Preoperative total protein (g/L)	65.91 $\pm$ 6.26	64.60 $\pm$ 6.02	1.404	0.161
Preoperative albumin (g/L)	40.30(37.55,43.05)	40.05(36.4,42.55)	-0.892	0.373
Preoperative cholesterol (mmol/L)	3.96 $\pm$ 0.72	3.93 $\pm$ 0.86	0.274	0.784
Preoperative creatinine clearance rate (mL/min)	86.47 $\pm$ 31.96	86.45 $\pm$ 29.72	0.006	0.995
Preoperative cardiac function (ejection fraction) (%)	61(56.0,64.5)	62(57,65)	-0.643	0.520
Intraoperative Data:				
Total operation time (min)	472(417.5,529.5)	452.5(400,525)	-0.976	0.329
Cardiopulmonary bypass time (min)	224(195,251.5)	216.5(193,246.25)	-0.96	0.337

Preoperative Data:	Non-SWC group (n = 185)	SWC group (n = 58)	t/z/χ^2	P value
Aortic cross-clamp time (min)	136(119,154)	137(120.25,149)	-0.132	0.895
Rewarming time (min)	85(69.5,100.5)	79(63.75,92.25)	-1.963	0.050
Intraoperative blood loss (mL)	500(337.5,800)	500(400,800)	-0.192	0.847
Total intraoperative transfusion volume (mL)	800(400,1197.5)	830(487.50,1223.75)	-0.544	0.586
Anesthesia recovery time (min)	195(112.5,307.5)	205(120,302.5)	-0.276	0.783
Duration of mechanical ventilation (min)	1150(976.5,3090.5)	1380(978.75,3628.75)	-0.735	0.462
Endotracheal intubation time (min)	1150(976.5,3090.5)	1447.5(987.5,4016.25)	-1.119	0.263
ICU length of stay (min)	6750(5201.5,9662.5)	8105(5348.75,11086.25)	-1.579	0.114
Postoperative Data:				
Total drainage volume, Postoperative day (POD) 1 (mL/day)	330(222.5,475)	417.5(258.75,597.5)	-1.91	0.056
Total drainage volume, POD 2 (mL/day)	250(137.5,467.5)	395(198.75,617.5)	-2.732	0.006
Total drainage volume, POD 3 (mL/day)	120(46,345)	172.5(73.75,423.75)	-1.647	0.100
Total postoperative transfusion volume (mL)	600(300,1000)	525(237.5,1100)	-0.29	0.772
Blood glucose, POD 1 (mmol/L)	9.5(8.2,11.1)	9.5(7.9,10.625)	-0.821	0.412
Blood glucose, POD 2 (mmol/L)	8.9(7.9,10.4)	8.9(7.65,10.1)	-0.715	0.474
Blood glucose, POD 3 (mmol/L)	8.4(7.25,10.15)	8.65(7.40,10.03)	-0.519	0.604
Lactate, POD 1 (mmol/L)	2.7(1.8,3.9)	2.1(1.475,3.2)	-2.027	0.043
Lactate, POD 2 (mmol/L)	1.4(1,1.8)	1.25(0.9,1.725)	-0.502	0.616
Lactate, POD 3 (mmol/L)	1(0.8,1.4)	1(0.7,1.425)	-0.631	0.528

Preoperative Data:	Non-SWC group (n = 185)	SWC group (n = 58)	t/z/ χ^2	P value
Hemoglobin, POD 1 (g/L)	101(92.5,114)	99(89,107)	-2.021	0.043
Hemoglobin, POD 2 (g/L)	98(88,108)	92.5(85,101)	-1.957	0.050
Hemoglobin, POD 3 (g/L)	93(85,103)	91.5(84.75,99.25)	-0.957	0.338
Total protein, POD 1 (g/L)	58.65(55.1,63.55)	57.1(53.85,60.93)	-1.677	0.093
Total protein, POD 2 (g/L)	60.29 $\pm$ 5.56	59.39 $\pm$ 6.30	1.039	0.300
Total protein, POD 3 (g/L)	60.8(57.82,64.70)	59.60(56.38,63.13)	-1.85	0.064
Creatinine clearance rate, POD 1 (mL/min)	65.30 $\pm$ 32.35	62.50 $\pm$ 27.19	0.596	0.552
Creatinine clearance rate, POD 2 (mL/min)	62.9(40.15,85.08)	66.05(40.97,82.50)	-0.384	0.701
Creatinine clearance rate, POD 3 (mL/min)	67.45 $\pm$ 31.91	64.56 $\pm$ 28.30	0.615	0.539

Composition of the Primary Outcome

Among the 58 patients who developed SWC, the most common category was wound exudation or fat liquefaction (36 cases, 62.1%), followed by wound healing failure or dehiscence (14 cases, 24.1%) and sternal dehiscence (8 cases, 13.8%). SWC categories were mutually exclusive and assigned according to the most severe wound manifestation, with each patient counted in only one category. Regarding interventions, 27 patients (46.6%) underwent debridement and primary suture, 8 patients (13.8%) required flap reconstruction for sternal dehiscence, and 4 of these (50.0% of dehiscence cases, 6.9% of all SWC) underwent redo sternal fixation/debridement in addition to flap reconstruction. Notably, 23 patients (39.7%) with wound exudation or fat liquefaction did not receive invasive interventions and were managed conservatively. The detailed composition of the primary outcome is presented in Table 2.

Table 2

Composition of the Primary Outcome (Sternal Wound Complications). Data are presented as n (%).

Percentages for each category are calculated based on the total 58 SWC cases. Percentages for interventions (Debridement/Primary Suture, Flap Reconstruction, Redo Sternotomy, and Conservative Management) are calculated within each category (row percentages). The three SWC categories are mutually exclusive and assigned according to the most severe wound manifestation; each patient was counted in only one category. The intervention columns may have hierarchical/inclusive relationships: for instance, all patients with sternal dehiscence underwent flap reconstruction, and some of them further received redo sternotomy in addition to flap reconstruction (i.e., redo sternotomy was an additional procedure following flap reconstruction, rather than an independent intervention category). Conservative management includes routine dressing changes or observation without invasive intervention. SWC, sternal wound complications.

Category	n (%)	Debridement / Primary Suture	Flap Reconstruction	Redo Sternotomy	Conservative Management
Wound exudation / fat liquefaction	36 (62.1)	13 (36.1)	0	0	23 (63.9)
Wound healing failure / dehiscence	14 (24.1)	14 (100)	0	0	0
Sternal dehiscence	8 (13.8)	0	8 (100)	4 (50.0)	0
Total	58 (100)	27 (46.6)	8 (13.8)	4 (6.9)	23 (39.7)

Identification of Independent Predictors for Sternal Wound Complications

A total of 12 candidate variables with $P < 0.1$ in univariate analysis were identified. Spearman's correlation analysis was first performed to assess collinearity among variables, with the correlation matrix presented as a heatmap (Fig. 2a). Among the candidate variables, height was highly correlated with body surface area ($r = 0.761$), hemoglobin Day1 was highly correlated with hemoglobin Day2 ($r = 0.779$), drainage Day1 was moderately correlated with drainage Day2 ($r = 0.514$), and total protein Day1 was moderately correlated with total protein Day3 ($r = 0.560$). After collinearity screening combined with clinical mechanistic judgment, the following 7 variables were excluded: height and body surface area (highly correlated with each other and lacked clear mechanistic support for SWC); hemoglobin Day2 (highly correlated with Day1 and less clinically relevant); drainage Day1 (moderately correlated with Day2 and had less significant between-group difference); total protein Day1 and Day3 (intercorrelated and non-specific indicators); and preoperative hemoglobin (largely covered by intraoperative factors). Previous surgery history and lactate Day1, although not statistically significant in the multivariable analysis, were retained at this stage due to the absence of collinearity issues and their clinical mechanistic plausibility, and were thus entered into the multivariable regression.

After the above screening, five variables were entered into a multivariable logistic regression model using the Enter method, yielding an EPV of $58/5 = 11.6$, which met the recommended minimum of 10,

with results presented as a forest plot (Fig. 2b).

Multivariable analysis revealed that three variables were independent predictors of in-hospital SWC: rewarming time (OR = 0.983 per minute, 95% CI: 0.970–0.996, $P = 0.012$), postoperative day 2 drainage output (OR = 1.002 per mL, 95% CI: 1.001–1.003, $P = 0.002$; equivalent to OR = 1.22 per 100 mL, 95% CI: 1.10–1.35), and postoperative day 1 hemoglobin (OR = 0.976 per g/L, 95% CI: 0.954–0.998, $P = 0.035$). All three variables were incorporated into the final nomogram.

Model Performance and Internal Validation

The nomogram model for predicting SWC risk is presented in Fig. 3a. The model demonstrated moderate discriminative ability, with an AUC of 0.702 (95% CI: 0.630–0.775) (Fig. 3b). Internal validation using 1000 bootstrap resamples yielded an optimism-corrected AUC of 0.713, with an optimism of -0.010. Calibration analysis showed good agreement between predicted probabilities and observed outcomes, with a calibration intercept of -0.115, a calibration slope of 0.888, a Brier score of 0.170, and a mean absolute error (MAE) of 0.035 (Fig. 3c). The Hosmer–Lemeshow test indicated adequate model fit ($\chi^2 = 6.722$, $P = 0.567$). Decision curve analysis (DCA) demonstrated threshold-dependent net benefit: the model provided positive net benefit at threshold probabilities below approximately 0.4, but within the 0.4–0.6 range, the net benefit fell below that of the “intervention none” strategy (Fig. 3d).

Development of the Simplified Scoring System

As an exploratory secondary analysis, the nomogram prediction model was converted into a simplified risk scoring system. The optimal cut-off values for the continuous predictors were determined by maximizing Youden's index on their respective receiver operating characteristic (ROC) curves. The criteria were defined as follows: rewarming time ≤ 83.5 minutes, postoperative day 2 drainage output > 261.5 mL, and postoperative day 1 hemoglobin ≤ 109.5 g/L. Each criterion met was assigned 1 point, resulting in a total risk score ranging from 0 to 3. Based on the total score, patients were stratified into three risk tiers: low-risk (0 points), intermediate-risk (1–2 points), and high-risk (3 points). Of note, these cut-off values were determined exploratorily in the present dataset and may carry optimism bias due to sample specificity; they should not be adopted as fixed thresholds for clinical decision-making until confirmed by external validation.

The simplified 0–3 point scoring system demonstrated moderate discriminative ability, with an AUC of 0.699 (95% CI: 0.635–0.763) (Fig. 3e). As shown in Table 3, the event rate showed an increasing trend across the three risk groups. The event rate was 6.7% (95% CI: 0.2–32.0%) in the low-risk group, 21.7% (95% CI: 16.1–28.4%) in the intermediate-risk group, and 38.6% (95% CI: 24.4–54.5%) in the high-risk group. The Cochran–Armitage trend test yielded $\chi^2 = 8.166$, $P = 0.004$. Compared with the low-risk group, the high-risk group had a significantly higher event rate (RR = 5.76, 95% CI: 2.58–10.98, $P = 0.024$ by Fisher's exact test). The intermediate-risk group showed a higher event rate than the low-risk group but the difference did not reach statistical significance (RR = 3.24, 95% CI: 0.47–22.28, $P = 0.315$).

Table 3

Risk Stratification and Incidence of Sternal Wound Complications Based on the Simplified Scoring System. Event rates and 95% CIs were calculated using the exact binomial (Clopper-Pearson) method. RR 95% CIs were calculated using bias-corrected and accelerated (BCa) bootstrap with 2000 resamples. P values were calculated using Fisher's exact test, comparing each risk group to the low-risk group. Of note, interpretation of RR estimates and the trend test should be cautious, as the low-risk group contained only 15 patients with a single event.

Risk Stratification (Score)	n	Events	Event rate % (95% CI)	RR (95% CI)	P Value
Low-risk (0)	15	1	6.7 (0.2–32.0)	1.00	–
Intermediate-risk (1–2)	184	40	21.7 (16.1–28.4)	3.24 (0.47–22.28)	0.315
High-risk (3)	44	17	38.6 (24.4–54.5)	5.76 (2.58–10.98)	0.024
Trend Test (Cochran–Armitage)				$\chi^2 = 8.166$, df = 1	0.004

Discussion

Based on a retrospective analysis of 243 patients who underwent aortic dissection surgery, this study developed a prediction model for SWC using early postoperative objective indicators. Multivariable logistic regression analysis revealed that rewarming time (OR = 0.983 per minute, 95% CI: 0.970–0.996, $P = 0.012$), postoperative day 2 drainage output (OR = 1.002 per mL, 95% CI: 1.001–1.003, $P = 0.002$; equivalent to OR = 1.22 per 100 mL, 95% CI: 1.10–1.35), and postoperative day 1 hemoglobin (OR = 0.976 per g/L, 95% CI: 0.954–0.998, $P = 0.035$) were all independent predictors of in-hospital SWC. The nomogram showed moderate discrimination and acceptable calibration upon internal validation, while the simplified scoring system showed modest discrimination and an increasing event-rate gradient across risk categories.

Rewarming time was inversely associated with SWC risk (OR = 0.983), indicating that shorter rewarming time was linked to higher SWC risk. During aortic dissection surgery with hypothermic circulatory arrest, rewarming is a critical phase for restoring normal physiology. Experimental evidence suggests that rewarming rate modulates inflammation following ischemia-reperfusion injury. Rapid rewarming has been shown to exacerbate neurological injury and inflammatory responses in animal models [11, 12], while slower rewarming is associated with attenuated systemic inflammation [13]. These findings support the hypothesis that rapid rewarming may provoke excessive inflammation and ischemia-reperfusion injury, thereby compromising tissue perfusion and immune defense. Thus, rewarming time may serve as a composite indicator of intraoperative management rather than an independent technical parameter. However, the absence of data on lowest nasopharyngeal temperature, circulatory arrest time, and rewarming rate precludes definitive causal inference, and further prospective studies are warranted.

The association between anemia and adverse outcomes after cardiac surgery is well established. Padmanabhan et al. [14] and Miceli et al. [15] independently reported that preoperative anemia was associated with long-term mortality and major complications following cardiac surgery. However, these studies focused primarily on baseline preoperative anemia rather than early postoperative hemoglobin levels.

In the present study, postoperative day 1 hemoglobin was identified as an independent predictor, together with rewarming time and drainage Day2. Aortic dissection surgery frequently involves prolonged cardiopulmonary bypass, hemodilution, and substantial blood loss, resulting in a marked and variable decline in hemoglobin levels. Postoperative day 1 hemoglobin thus integrates both preoperative baseline status and intraoperative losses, more accurately reflecting the patient's actual oxygen-carrying capacity.

At the tissue level, reduced hemoglobin compromises local oxygen delivery to the surgical wound, which in turn impairs neutrophil bactericidal function and tissue repair capacity. Younis et al. [16] reviewed that hypoxia impairs repair cell activity, reduces angiogenesis, and increases infection risk, thereby hindering wound healing. Hajdamowicz et al. [17] and Lodge et al. [18] demonstrated that hypoxia significantly compromises neutrophil clearance of *Staphylococcus aureus*, and Zhu et al. [19] systematically summarized the molecular mechanisms by which hypoxia regulates neutrophil function. In the aortic dissection population, early postoperative coagulopathy, systemic inflammation, and hemodilution frequently co-exist, and a marked hemoglobin decline may further amplify these risks. Moreover, this early time point falls within a potentially actionable window for early risk stratification.

Postoperative day 2 drainage output was significantly higher in the SWC group than in the non-SWC group in univariate analysis (395 mL vs. 250 mL, $P = 0.006$), and showed an independent positive association in multivariable analysis (OR = 1.002 per mL, 95% CI: 1.001–1.003, $P = 0.002$; equivalent to OR = 1.22 per 100 mL, 95% CI: 1.10–1.35), suggesting that increased drainage output was independently associated with higher SWC risk. In a cohort of 1,188 cardiac surgery patients, Christensen et al. [20] reported that postoperative drainage exceeding 200 mL/h was independently associated with 30-day mortality, stroke, and reoperation for exploration, further supporting the potential value of increased drainage output as a warning sign of adverse postoperative outcomes, which is contextually consistent with our observations.

The association between increased drainage and higher SWC risk has a potential pathophysiological basis; however, the following mechanisms remain hypothesis-generating in the present dataset. First, chest tube drainage contains various pro-inflammatory cytokines. Goldstein et al. [21] demonstrated that levels of IL-1 β , IL-5, IL-8, and IL-13 in drainage fluid were positively correlated with drainage duration in pediatric cardiac surgery patients, indicating that high output may reflect the intensity of local inflammation. Second, increased drainage often suggests incomplete hemostasis or inadequate evacuation. Retained blood syndrome, with an incidence of 13.8%–22.7% after cardiac surgery, can lead to a series of inflammatory complications, including infection [22]. Third, patients with high drainage

output typically require prolonged chest tube retention. Tschudin-Sutter et al. [23] confirmed that drainage retention exceeding 48 hours is an independent risk factor for severe sternal wound infection after cardiac surgery, indicating that extended tube retention itself significantly increases the opportunity for exogenous infection. These mechanistic pathways require direct validation in future studies with dedicated measurements of the relevant mediators.

Several predictive models for sternal wound complications (SWC) after cardiac surgery have been previously reported, yet most are subject to important limitations. Existing risk assessment tools, such as the EuroSCORE II, rely predominantly on preoperative static factors—including age, urgent status, left ventricular dysfunction, prior cardiac surgery, diabetes, respiratory disease, and female sex [4, 24]—and fail to incorporate intraoperative stress or dynamic postoperative physiological changes. Furthermore, most available models are confined to specific surgical populations, particularly coronary artery bypass grafting (CABG), and focus on deep sternal wound infection (DSWI) as a single outcome rather than the full spectrum of SWC. For instance, Kalisnik et al. [10] developed a machine learning model for DSWI prediction in CABG patients with good discrimination (AUC = 0.851), yet its applicability to aortic dissection patients remains unknown.

In the aortic dissection population, Lin et al. [25] reported that delayed sternal closure was associated with prolonged cardiopulmonary bypass and aortic cross-clamp time, as well as increased ECMO support—factors that may compromise tissue healing and elevate infection risk. Wu et al. [26] further demonstrated that intraoperative platelet transfusion significantly increased the incidence of sternal wound infection in type A aortic dissection patients after total arch replacement. Additionally, accumulating evidence has shown that dynamic perioperative indicators—including cardiopulmonary bypass time, intraoperative anemia, and postoperative C-reactive protein levels—are closely associated with DSWI risk [5], yet these variables are frequently overlooked in current risk stratification systems [6, 8].

To address these gaps, the present study developed a SWC prediction model specifically tailored to the Stanford type A aortic dissection population, incorporating early postoperative objective indicators that are readily available in routine clinical practice. This study provides a preliminary exploration in this direction.

Limitations

This study has several limitations. First, as a single-center retrospective study, the generalizability of our findings may be limited, and external validation in independent cohorts is needed. Second, the primary outcome was a composite endpoint comprising three conditions—wound exudation/fat liquefaction, wound healing failure/dehiscence, and sternal dehiscence—with different severity and pathophysiology, which may introduce heterogeneity. Third, no routine post-discharge surveillance was conducted, and all events were identified only during the index hospitalization; thus, delayed SWC occurring after discharge may have been underestimated. Fourth, the simplified scoring system was derived as an exploratory

analysis, its DCA showed limited net benefit beyond low threshold ranges, and the model has only been internally validated without external confirmation of its generalizability, indicating modest clinical utility. Fifth, the specific duration of deep hypothermic circulatory arrest (DHCA) was not consistently documented in our institutional database and could not be included in the analysis. Detailed perioperative glucose data were also not available in our retrospective dataset and could not be adjusted for. Sixth, due to the limited sample size, we did not perform subgroup analyses stratified by surgical procedure type (e.g., isolated ascending aortic replacement, root replacement, or total arch replacement). The heterogeneity of surgical techniques may have influenced the occurrence of SWC, and future studies with larger cohorts are needed to explore the impact of different surgical procedures on SWC risk.

Conclusion

This study identified rewarming time, postoperative day 2 drainage output, and postoperative day 1 hemoglobin as independent predictors of in-hospital SWC after aortic dissection. The nomogram incorporating these three variables demonstrated moderate discriminative ability and good calibration upon internal validation, supporting its potential utility as an internally validated exploratory model for early risk stratification. The simplified scoring system derived from the model showed modest performance as an exploratory tool and requires prospective external validation before clinical application.

Declarations

Availability of Data and Materials

The datasets generated and/or analyzed during the current study are not publicly available due to patient privacy and ethical restrictions imposed by the institutional review board. De-identified data may be made available from the corresponding author upon reasonable request, subject to institutional data access policies and approval.

Author Contributions

This study was conceptualized and designed by Yuji Xiao and Juan Luo, with Yuji Xiao drafting the initial manuscript and performing data analysis. Data curation was performed by Wanru Ma, Jinzhi Yin, and Jia Liu. Hongzhen Wei and Juan Wu contributed to data interpretation and manuscript revision. Yaoguang Feng, as the departmental director, provided overarching supervision, resources, and critical guidance. Juan Luo, as the corresponding author, supervised the entire research process and finalized the manuscript. All authors have read and approved the final version.

Ethics Approval and Consent to Participate

This study was approved by the Ethics Review Committee of the First Affiliated Hospital of Hengyang Medical School, University of South China (approval number: 2024LL0410001). The requirement for informed consent was waived due to the retrospective nature of the study.

Acknowledgments

We gratefully acknowledge the colleagues from the Department of Cardiothoracic Surgery and the Medical Records Department of the First Affiliated Hospital of University of South China for their support and invaluable contributions to the implementation of this study.

Funding

This work was supported by the Natural Science Foundation of Hunan Province (Grant No. 2026JJ81427).

Conflict of Interest

The authors declare no conflict of interest.

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Figures

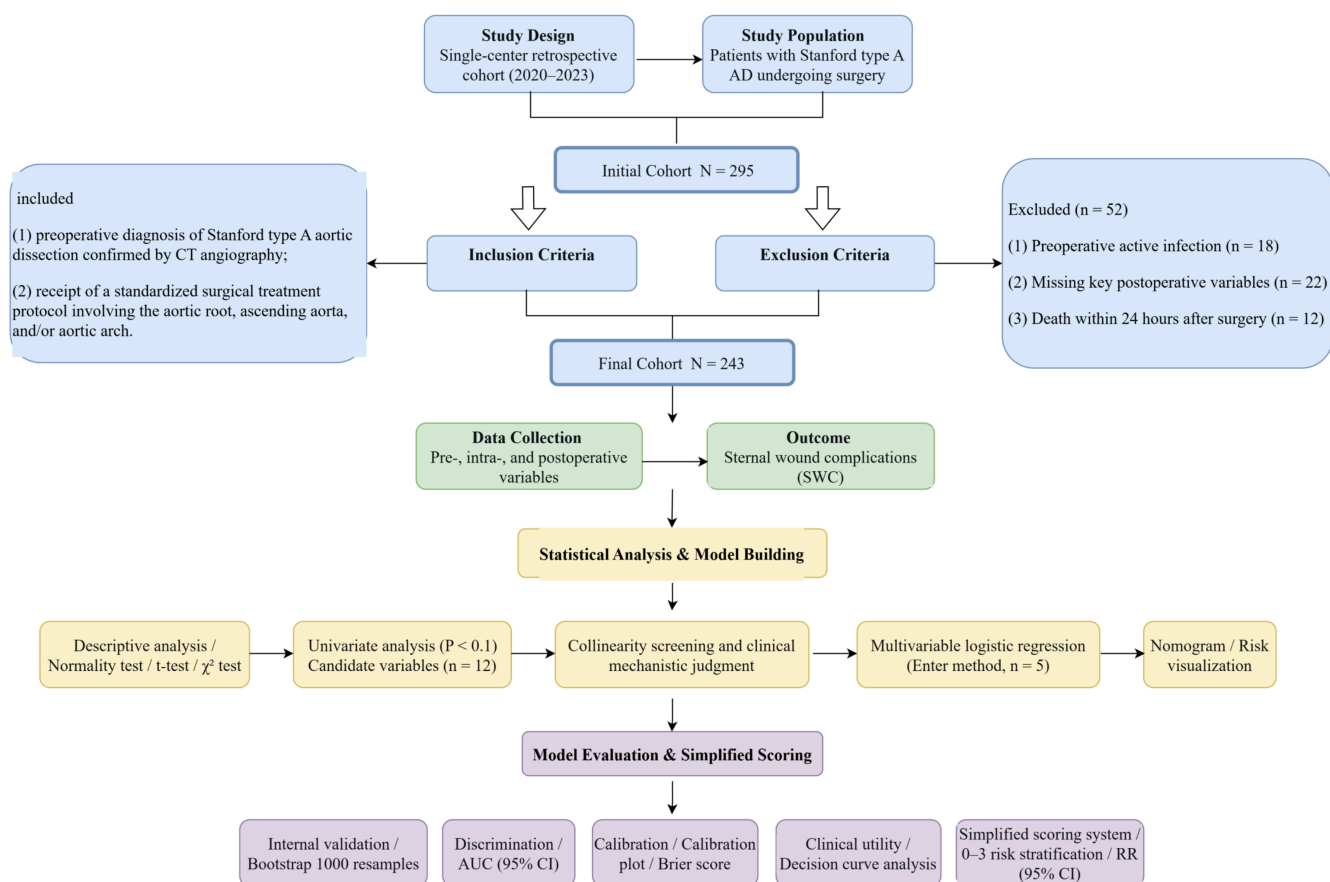


Figure 1

Flowchart of study design, patient screening, variable screening, and model development. Of the 295 patients in the initial screening cohort, 243 were included in the final analysis. The flowchart illustrates patient screening, variable screening, model construction, and validation.

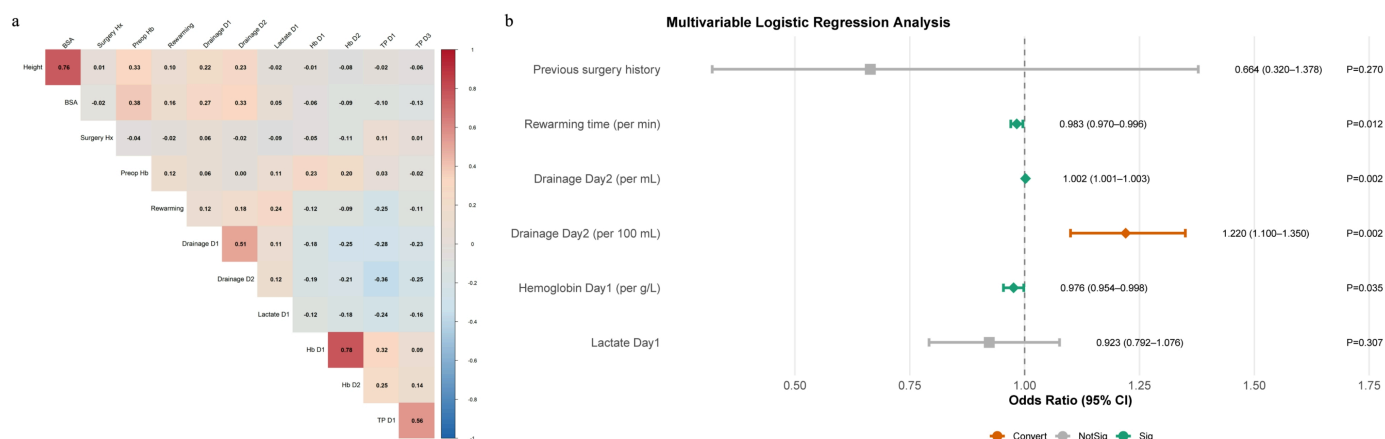


Figure 2

Variable screening and multivariable logistic regression analysis. (a) Spearman correlation heatmap of 12 candidate variables. Red indicates positive correlation, blue indicates negative correlation, with darker color representing stronger correlation; values within each cell are Spearman correlation coefficients. $r > 0.7$ indicates high collinearity (e.g., height vs. BSA: $r = 0.761$; hemoglobin Day1 vs. Day2: $r = 0.779$). (b) Forest plot of multivariable logistic regression analysis showing the five variables entered into the regression after collinearity screening and clinical mechanistic judgment. Green diamonds indicate statistically significant variables ($P < 0.05$); gray squares indicate non-significant variables ($P \geq 0.05$). Drainage Day2 is presented in both its original unit (per mL) and a clinically converted unit (per 100 mL), with the converted row highlighted in orange to distinguish it from the original variable. Rewarming time (OR = 0.983 per minute, 95% CI: 0.970–0.996, $P = 0.012$), drainage Day2 (OR = 1.002 per mL, 95% CI: 1.001–1.003, $P = 0.002$; equivalent to OR = 1.22 per 100 mL, 95% CI: 1.10–1.35), and hemoglobin Day1 (OR = 0.976 per g/L, 95% CI: 0.954–0.998, $P = 0.035$) were identified as independent predictors. The vertical dashed line indicates OR = 1. Abbreviations: POD, postoperative day; OR, odds ratio; CI, confidence interval; BSA, body surface area; Hb, hemoglobin; TP, total protein.

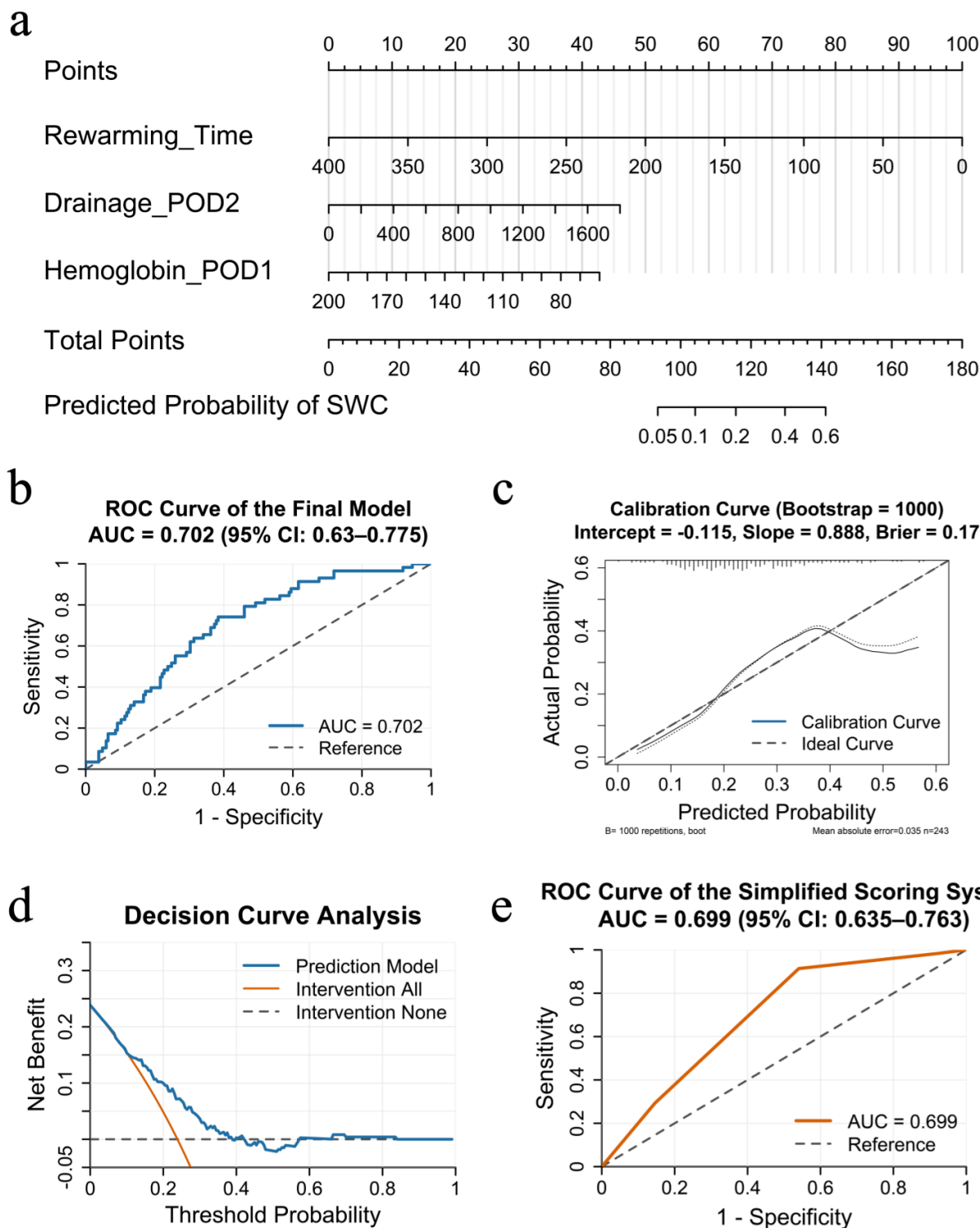


Figure 3

Nomogram for predicting sternal wound complications (SWC) risk after aortic dissection and its validation. (a) The predictive nomogram integrating rewarming time, POD2 drainage output, and POD1 hemoglobin; (b) ROC curve of the final model (AUC = 0.702, 95% CI: 0.630–0.775); (c) Calibration curve with 1000 bootstrap resamples (intercept = -0.115, slope = 0.888, Brier score = 0.170); (d) Decision curve

analysis demonstrating threshold-dependent net benefit, mainly below approximately 0.4; (e) ROC curve of the simplified scoring system (AUC = 0.699, 95% CI: 0.635–0.763).