


Clinical Nomogram for Early Identification of Necrotizing Soft Tissue Infections: Development and Internal Validation in Hospitalized Patients

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Purpose: To develop and validate a predictive model for necrotizing soft tissue infections (NSTIs) in hospitalized patients with skin and soft tissue infections (SSTIs).

Patients and Methods: In this retrospective single-center study, 131 patients with SSTIs admitted between April 2021 and March 2024 were divided into NSTI (n=72) and non-NSTI (n=59) groups. Demographic information, clinical characteristics, and key severity scores were collected. LASSO regression was used to select variables, and a logistic regression model was then developed. Model performance was evaluated using AUC, sensitivity, specificity, and the Hosmer-Lemeshow test. Internal validation was performed using 1000 bootstrap resamples. Model discrimination, calibration, and clinical utility were assessed through ROC curve, calibration curve, and decision curve analysis (DCA), respectively.

Results: Four independent predictors—age, temperature, depth of infection, and SOFA score—were identified. A nomogram constructed based on these variables exhibited good discriminative performance, with an AUC of 0.832 (95% CI: 0.763–0.900), a sensitivity of 0.722, and a specificity of 0.797. Internal validation revealed an AUC of 0.832 (95% CI: 0.752–0.897). The model passed the H-L test ($p = 0.322$). The calibration curve showed close alignment between predicted and observed outcomes (slope = 0.916), indicating good calibration. DCA demonstrated net clinical benefit across a wide range of threshold probabilities (0.1–0.9).

Conclusion: The predictive model is simple and practical, with good discriminative and calibration performance. It may serve as a useful decision-support tool for early identification of NSTIs. However, future multicenter prospective studies are still needed for external validation to assess its practical application value.

Keywords: skin and soft tissue infections, necrotizing soft tissue infections, sepsis, prediction model

Introduction

Necrotizing soft tissue infections (NSTIs) are a group of rapidly progressive and life-threatening infections caused by microbial pathogens, primarily affecting the skin, subcutaneous tissue, fascia, and muscle.¹ The incidence of NSTIs ranges from 0.86 to 32.64 per 100,000 person-years, which is influenced by factors such as climate and seasonal variations.² The disease often follows a fulminant clinical course and is frequently complicated by sepsis, septic shock, and multiple organ dysfunction syndrome, with mortality rates reported as high as 23.1%–30%.^{3,4} Although NSTIs are rare, they are markedly more severe than other types of skin and soft tissue infections (SSTIs), and any delay in diagnosis or treatment can worsen disease severity and outcomes.

Early identification of NSTIs remains a significant clinical challenge. Some patients may have no obvious history of trauma or may initially present with only mild, nonspecific symptoms such as erythema, swelling, localized pain, or fever.⁵ Notably, the severity of pain is often disproportionate to the apparent skin damage, and typical signs such as bullae, ecchymosis, skin necrosis, or subcutaneous crepitus may not appear until the disease is in an advanced stage.^{6,7} Timely surgical intervention is critical to reducing mortality and disability in NSTIs. However, it has been reported that

over 50% of NSTI cases are initially misdiagnosed as non-necrotizing soft tissue infections, delaying appropriate surgical and antimicrobial therapy and negatively affecting patient outcomes.^{8,9}

Among existing assessment tools, the Laboratory Risk Indicator for Necrotizing Fasciitis (LRINEC) score is currently regarded as one of the most useful screening tools for early detection of NSTIs. It incorporates six laboratory parameters—C-reactive protein, white blood cell count, hemoglobin, sodium, creatinine, and blood glucose—and a score ≥ 6 is considered highly suggestive of NSTIs.¹⁰ However, a recent systematic review and meta-analysis involving 23 studies ($n = 5982$) reported a sensitivity of 68.2% and specificity of 84.8% for LRINEC ≥ 6 .¹¹ Additionally, an 18-year retrospective study found that the sensitivity of LRINEC ≥ 6 was only 59% with a positive predictive value of 57%, indicating a substantial risk of missed diagnosis in clinical practice.¹² In addition to the LRINEC score, several models such as the modified LRINEC,¹³ SIARI,¹⁴ and NAS¹⁵ scores have been proposed. However, these tools have limited accuracy or lack extensive validation.

Recent studies have also explored the use of nomograms and artificial intelligence (AI) to improve the diagnosis of NSTIs. For example, MacLeod et al¹⁶ developed a nomogram incorporating age, C-reactive protein, and nonlinear albumin. However, its applicability is limited to people who inject drugs. Another study proposed an AI-based model capable of automatically detecting NSTI-related features on CT imaging.¹⁷ This approach relies on high-quality CT datasets and is more suitable for refining diagnostic certainty and assisting surgeons in delineating surgical margins on CT scans, rather than serving as an initial screening tool in the emergency setting. In addition, Wu et al¹⁸ identified several promising NSTI biomarkers based on biochemical analysis of infectious fluids. Nonetheless, procedures such as ultrasound-guided aspiration, fluid culture, and biochemical testing limit the model's clinical feasibility, and it remains unclear whether all NSTI subtypes produce suprafascial fluid. Therefore, a simple, reliable, and bedside-applicable diagnostic tool that integrates severity scoring with key clinical variables through an appropriate algorithm is still needed. To fill this gap, this study aimed to develop and validate a predictive nomogram to facilitate the early diagnosis of NSTIs and guide timely intervention.

Methods

Study Setting and Source of Data

This retrospective study utilized data extracted from the electronic medical record system of the First Affiliated Hospital of Wenzhou Medical University, a provincial tertiary (Level 3A) hospital with 3800 beds in Zhejiang Province, eastern China. Data were collected between March and August 2024. This study was reported in accordance with the TRIPOD guidelines.

Participants

The study populations were hospitalized patients with SSTIs admitted to the Emergency Department of the First Affiliated Hospital of Wenzhou Medical University between April 2021 and March 2024. Inclusion criteria were: (a) age ≥ 18 years; and (b) a diagnosis of SSTIs based on medical history, physical examination, and laboratory findings, etc. (the minimum criterion being a skin lesion with the typical inflammatory tetrad—tenderness, erythema, edema, and warmth).¹⁹ Patients with incomplete clinical data were excluded. Ultimately, a total of 131 patients with SSTIs were included in the study. Among them, 72 patients were diagnosed with NSTIs through surgical exploration. The patient enrollment process is shown in [Figure 1](#).

Outcome and Predictors

The outcome was the diagnosis of NSTIs. The length of hospital stay and mortality of patients were also collected but were not primary outcomes.

Potential predictors of NSTIs were selected based on literature review and clinical plausibility.^{20–22} These included demographic characteristics (sex, age), lifestyle (drinking, smoking), vital signs (respiratory rate, heart rate, axillary temperature, and mean arterial pressure), preoperative comorbidities (diabetes mellitus, hypertension, heart disease, chronic liver disease, and chronic kidney disease), laboratory values (C-reactive protein, white blood cell, procalcitonin,

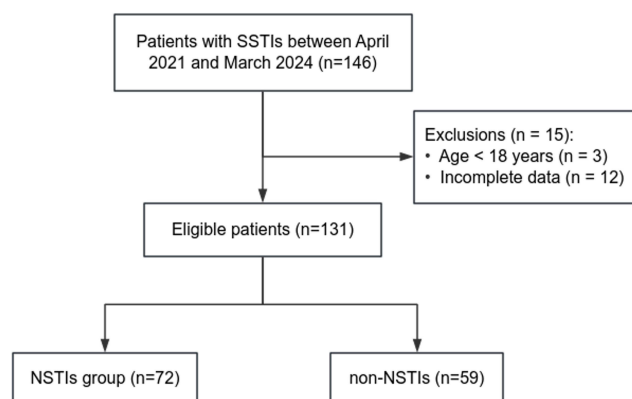


Figure 1 Patient enrollment flowchart.

and creatine kinase), deep of infection (skin or subcutaneous/fascia/muscle), treatment measures (non-invasive ventilation, invasive ventilation, hemodialysis), as well as disease severity (SOFA score, APACHE II score, LRINEC scores, and occurrence of shock).

Vital signs, SOFA, APACHE II, and LRINEC scores were the results measured at the time of admission. Mean arterial pressure is calculated as diastolic blood pressure plus one-third of the difference between systolic and diastolic blood pressures. Laboratory values were the worst results obtained within 24 hours of admission. The depth of infection was determined at admission based on local skin manifestations and finger compression/palpation examination. Skin-limited infection (skin) was characterized by localized erythema and pain with clear margins; on finger compression, skin tension was similar to that of surrounding tissue, without crepitus. Infection involving the subcutaneous tissue (subcutaneous/fascia/muscle) was characterized by localized erythema with purplish discoloration or ecchymosis, severe pain, and the presence of bullae or hemorrhagic blisters; on palpation, increased skin tension, softening of the subcutaneous tissue, and crepitus could be detected.^{23,24}

Entry of outcome variables was blinded. The outcome was collected separately from the other predictors to ensure that researchers did not know information about the other side when collecting the outcome or predictors.

Sample Size

The prediction model developed in this study included 4 predictors. According to the 10 times EPV principle, the sample should have at least 40 NSTI cases and 40 non-NSTI cases. Therefore, the sample size of the study met the statistical requirements.

Statistical Analysis

All statistical analyses were performed using SPSS 28.0 software and R 4.3.3 software.

(1) Univariate analysis: The Kolmogorov–Smirnov test was used to assess the normality of continuous variables. Variables with a normal distribution were expressed as mean \pm standard deviation (SD) and compared between groups using independent samples *t*-tests. Non-normally distributed continuous variables were presented as median with interquartile range (IQR) and compared using the Mann–Whitney *U*-test. Categorical variables were expressed as numbers and percentages (n, %) and compared using the chi-square test or Fisher’s exact test, as appropriate. Associations between variables and the outcome were quantified using odds ratios (OR) and corresponding 95% confidence intervals (CI).

(2) Model development: A ten-fold cross-validated least absolute shrinkage and selection operator (LASSO) regression was performed using the “glmnet” package in R to determine the optimal penalty parameter lambda (λ). Variables selected by LASSO regression were subsequently entered into a forward stepwise logistic regression model, and statistically significant predictors were retained to construct the risk scoring model, which was then visualized as

a nomogram. Logistic regression analyses were conducted using the `lrm()` function, and the nomogram was constructed using the `nomogram()` function in the “rms” package.

(3) Model evaluation and validation: The discrimination of model was assessed using the receiver operating characteristic (ROC), with sensitivity, specificity, the area under the curve (AUC), net reclassification improvement (NRI), and integrated discrimination improvement (IDI) calculated. Model calibration was evaluated using the Hosmer-Lemeshow (H-L) goodness-of-fit test and calibration curves. Decision curve analysis (DCA) and decision threshold heatmap were conducted to assess the clinical utility of the model. Internal validation was performed using 1000 bootstrap resamples.²⁵ ROC curve plotting and AUC calculation were performed using the “pROC” and “fROC” package; calibration curves were generated using the “rms” package; DCA was conducted with the “rmda” package; and decision threshold heatmap was generated using the “ggplot2” package. A sensitivity analysis was performed by adjusting for demographic factors and comorbidities to assess the robustness of the model. All statistical tests were two-sided, and a p -value < 0.05 was considered statistically significant.

Ethics Consideration

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Review Committee of the First Affiliated Hospital of Wenzhou Medical University (Approval No. KY2024-R194). A waiver for informed consent was allowed by the ethics review committee in view of the retrospective nature of the research and the anonymity of the data.

Results

Characteristics of Patients

The clinical data of 131 patients with SSTIs were retrospectively analyzed, including 83 (63.4%) males and 48 (36.6%) females. The median age was 62.0 years (IQR: 53.0, 74.0). Patients were categorized into NSTI ($n=72$) and non-NSTI ($n=59$) groups based on clinical features and surgical exploration findings. Univariate analyses revealed significant differences between NSTI and non-NSTI groups in several variables, including age (OR=0.965, 95% CI: 0.940–0.990), heart rate (OR=1.021, 95% CI: 1.004–1.038), temperature (OR=0.588, 95% CI: 0.386–0.896), chronic liver disease (OR=2.770, 95% CI: 1.204–6.370), depth of infection (OR=5.556, 95% CI: 2.382–12.957), procalcitonin (OR=1.004, 95% CI: 0.993–1.016), hemodialysis (OR=4.929, 95% CI: 1.573–15.448), SOFA (OR=1.208, 95% CI: 1.090–1.340), APACHE II (OR=1.100, 95% CI: 1.035–1.168), LRINEC (OR=1.167, 95% CI: 1.041–1.308), and shock (OR=3.592, 95% CI: 1.684–7.663). Furthermore, the NSTI group had a longer length of stay and a higher mortality rate than the non-NSTI group, although only the difference in length of stay was statistically significant ($p = 0.006$). Detailed results are shown in Table 1.

Table 1 Baseline Characteristics of Patients

Characteristics	Overall (n=131)	Non-NSTI Group (n=59)	NSTI Group (n=72)	p-value
Sex, n (%)				0.385
Male	83 (63.4)	35 (59.3)	48 (66.7)	
Female	48 (36.6)	24 (40.7)	24 (33.3)	
Age, median (IQR), y	62.0 (53.0, 74.0)	66.0 (60.0, 79.0)	56.5 (50.3, 68.0)	<0.001
Lifestyle, n (%)				
Drinking	38 (29.0)	13 (22.0)	25 (34.7)	0.111
Smoking	36 (27.5)	17 (28.8)	19 (26.4)	0.757
Vital signs				
RR, median (IQR), n/min	20.0 (20.0, 25.0)	20.0 (20.0, 25.0)	21.5 (20.0, 36.0)	0.173
HR, median (IQR), n/min	95.0 (82.0, 108.0)	89.0 (80.0, 104.0)	100.0 (86.3, 116.0)	0.015
T, median (IQR), °C	37.3 (36.8, 37.9)	37.5 (37.0, 38.1)	37.2 (36.7, 37.9)	0.010
MAP, mean (SD), mmHg	89.1 (18.2)	91.8 (18.5)	87.0 (17.8)	0.134

(Continued)

Table 1 (Continued).

Characteristics	Overall (n=131)	Non-NSTI Group (n=59)	NSTI Group (n=72)	p-value
Comorbidities, n (%)				
Diabetes mellitus	46 (35.1)	17 (28.8)	29 (40.3)	0.171
Hypertension	53 (40.5)	25 (42.4)	28 (38.9)	0.686
Gastrointestinal disease	15 (11.5)	8 (13.6)	7 (9.7)	0.493
Heart disease	15 (11.5)	7 (11.9)	8 (11.1)	0.893
Chronic liver disease	36 (27.5)	10 (16.9)	26 (36.1)	0.015
Chronic kidney disease	9 (6.9)	2 (3.4)	7 (9.7)	0.184
Depth of infection, n (%)				<0.001
Skin	86 (65.6)	50 (84.7)	36 (50.0)	
Subcutaneous/fascia/muscle	45 (34.4)	9 (15.3)	36 (50.0)	
Laboratory values				
CRP, median (IQR), mg/L	155.4 (76.2, 240.0)	139.9 (41.0, 219.9)	162.0 (102.0, 249.2)	0.112
WBC, median (IQR), ×10 ⁹ /L	11.2 (6.6, 18.0)	11.0 (6.8, 16.7)	11.7 (5.5, 19.7)	0.945
PCT, median (IQR), ng/mL	4.2 (0.4, 23.2)	1.6 (0.1, 21.9)	11.1 (1.4, 29.9)	0.005
CK, median (IQR), U/L	95.0 (38.0, 273.0)	95.0 (50.0, 478.0)	92.0 (29.3, 414.0)	0.803
SOFA, median (IQR)	3.0 (2.0, 8.0)	2.0 (1.0, 5.0)	5.0 (2.0, 9.0)	<0.001
APACHE II, median (IQR)	12.0 (8.0, 17.0)	10.0 (7.0, 15.0)	14.5 (9.0, 19.0)	0.001
LRINEC, median (IQR)	6.0 (3.0, 9.0)	5.0 (2.0, 7.0)	6.0 (4.0, 9.0)	0.009
Shock, n (%)	52 (39.7)	14 (23.7)	38 (52.8)	<0.001
Treatment, n (%)				
Non-invasive ventilation	24 (18.3)	9 (15.3)	15 (20.8)	0.411
Invasive ventilation	33 (25.2)	12 (20.3)	21 (29.2)	0.247
Hemodialysis	23 (17.6)	4 (6.8)	18 (26.4)	0.003
Length of stay, median (IQR), d	12.0 (6.0, 23.0)	10.0 (6.0, 16.0)	18.0 (6.25, 31.0)	0.006
Death, n (%)	44 (33.6)	15 (25.4)	29 (40.3)	0.073

Abbreviations: IQR, interquartile range; SD, standard deviation; RR, respiratory rate; HR, heart rate; T, temperature; MAP, mean arterial pressure; NSTI, necrotizing soft tissue infection; CRP, C-reactive protein; PCT, procalcitonin; CK, creatine kinase; SOFA, Sequential Organ Failure Assessment; APACHE II, Acute Physiology and Chronic Health Evaluation II; LRINEC, Laboratory Risk Indicator for Necrotizing Fasciitis.

Selection of Predictors

A cross-validated LASSO regression was performed using the 11 significant factors from [Table 1](#) to identify variables for the prediction model. As shown in [Figure 2A](#), the minimum criteria (λ_{\min}) and the one-standard-error criteria (λ_{1se}) corresponded to models containing 8 and 3 variables, respectively. Given that the model selected at λ_{\min} demonstrated the best predictive accuracy, we selected the 8 variables it included: depth of infection, temperature, chronic liver disease, LRINEC score, SOFA score, age, APACHE II score, and hemodialysis ([Figure 2B](#)).

Development of Prediction Model

Stepwise forward logistic regression was performed using the 7 variables selected by LASSO regression. Ultimately, four statistically significant independent risk factors were identified and included in the final logistic regression model: depth of infection, age, SOFA score, and temperature (see [Table 2](#)). The risk prediction formula based on these four variables is as follows:

$$P = 1/[1 + \exp(-26.575 - 1.849 \times \text{Depth of infection} + 0.060 \times \text{Age} - 0.166 \times \text{SOFA score} + 0.640 \times \text{Temperature})].$$

To facilitate clinical application, a nomogram was constructed based on this model. As depicted in [Figure 3](#), each variable corresponds to a specific number of points according to the patient's characteristics. The total score is obtained by summing the individual points, which can then be used to estimate the probability of NSTIs in a given patient (An example is provided in the [Supplementary Materials Figure S1](#)).

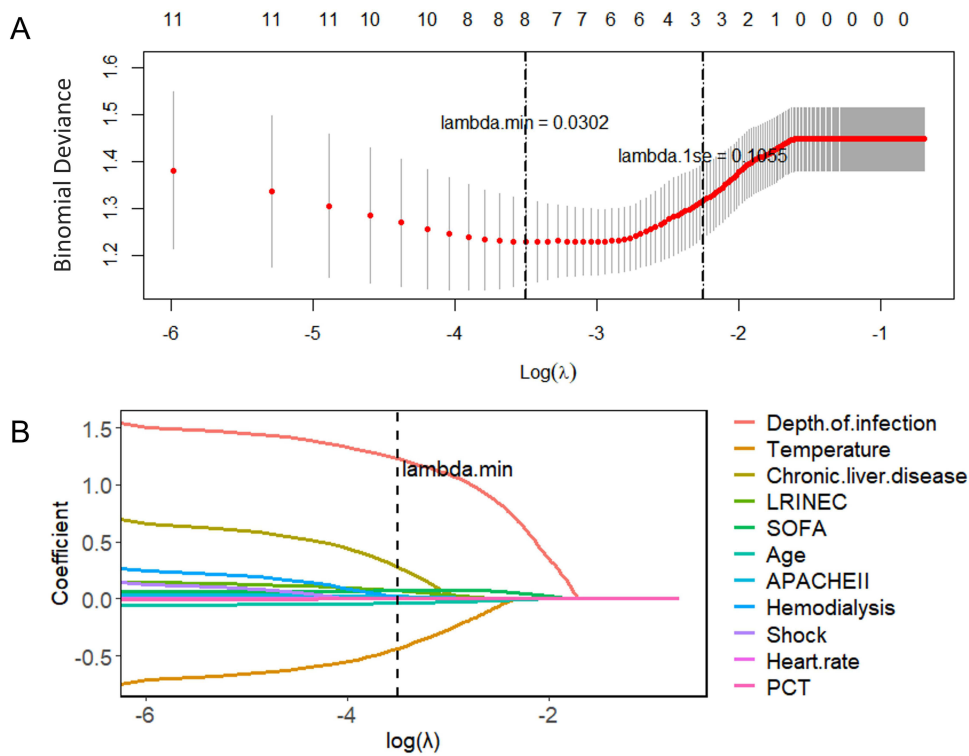


Figure 2 Variable selection using the least absolute shrinkage and selection operator (LASSO) regression. **(A)** The binomial deviance curve obtained from ten-fold cross-validation is plotted against $\log(\lambda)$. The left dotted line indicates the value of λ that minimizes the mean cross-validated binomial deviance (λ_{\min}), corresponding to a model with 8 non-zero coefficients. The right dotted line represents the largest value of λ within one standard error of the minimum (λ_{1se}), corresponding to a model with 3 non-zero coefficients. **(B)** LASSO coefficient profiles of the 11 candidate variables.

Model Evaluation and Validation

The nomogram model achieved an AUC of 0.832 (95% CI: 0.763–0.900), with a sensitivity of 0.722 (95% CI: 0.613–0.825) and a specificity of 0.797 (95% CI: 0.689–0.891). In contrast, the SOFA score (AUC=0.698, 95% CI: 0.609–0.788), APACHE II score (AUC=0.662, 95% CI: 0.570–0.755), and LRINEC score (AUC=0.632, 95% CI: 0.537–0.727) demonstrated relatively lower performance (Figure 4A). The NRI and IDI analyses demonstrated that the nomogram was significantly improved compared with the three scoring systems (Table 3).

Internal validation was performed using 1000 bootstrap resamples. As shown in Figure 4B, the AUC of the nomogram was 0.832 (95% CI: 0.752–0.897), further confirming its strong discriminative ability.

The H-L test yielded a chi-square value of 9.245 with a p-value of 0.322, suggesting an adequate model fit. Calibration was assessed using a calibration curve generated from 1000 bootstrap samples. In Figure 4C, the bias-corrected curve closely aligned with the ideal reference line, with a slope of 0.916, indicating good agreement between predicted and observed outcomes.

Table 2 Results of the Multivariate Logistic Regression

Variables	B	Wald	OR	95% CI	p-value
Depth of infection	1.849	13.553	6.354	2.374–17.005	<0.001
Age	-0.060	13.272	0.942	0.912–0.973	<0.001
SOFA	0.166	8.413	1.181	1.055–1.321	0.004
Temperature	-0.640	5.456	0.527	0.308–0.902	0.020
Intercept	26.575	6.331			0.012

Abbreviation: SOFA, Sequential Organ Failure Assessment.

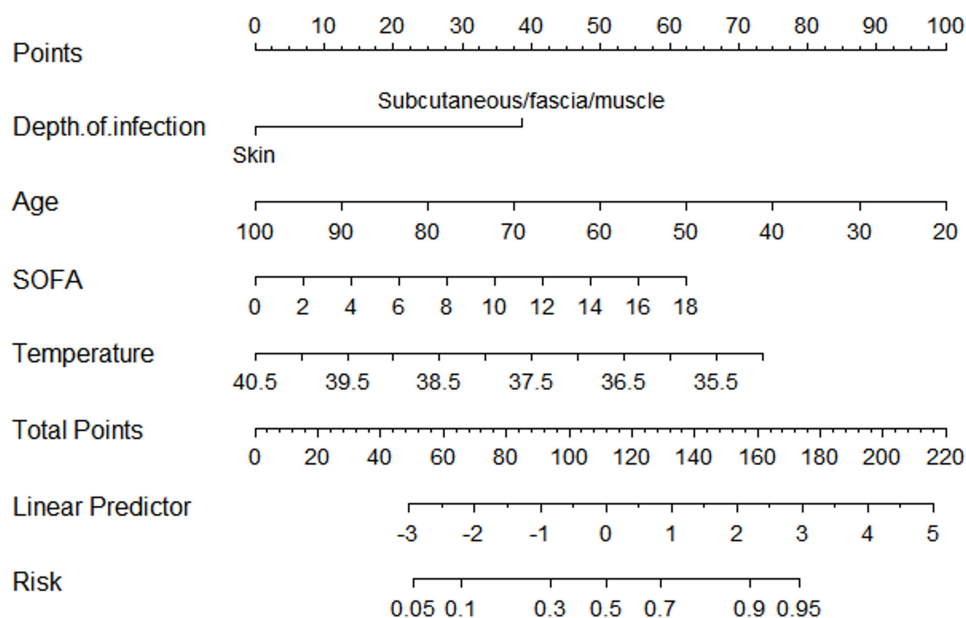


Figure 3 Nomogram for predicting the risk of necrotizing soft tissue infections.

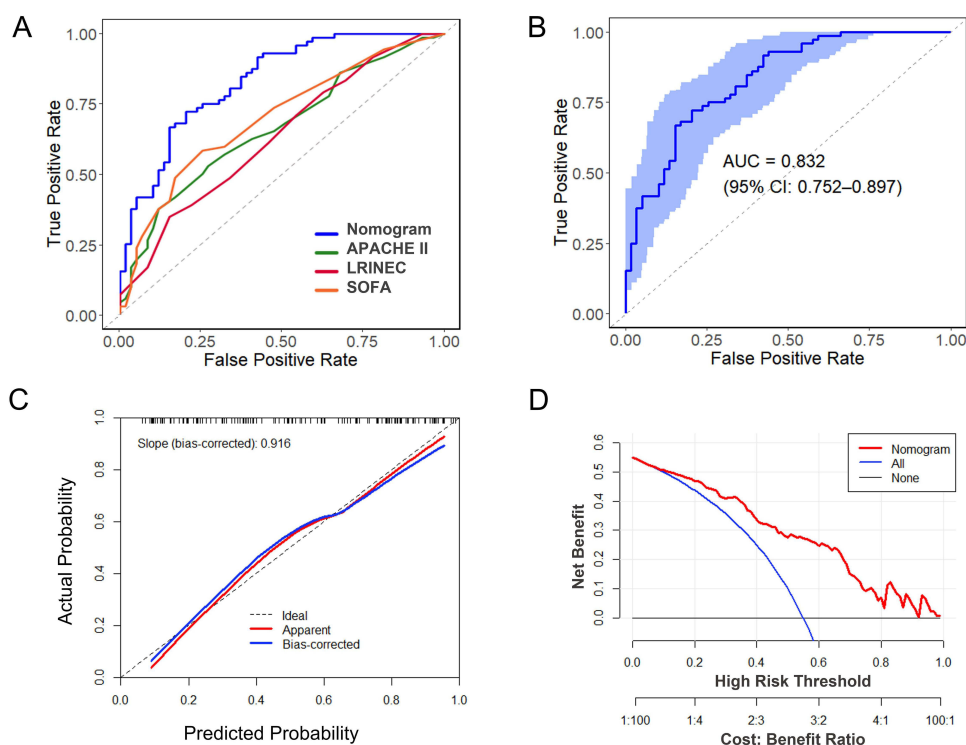


Figure 4 Evaluation and internal validation of the nomogram model. **(A)** Receiver operating characteristic curve of the nomogram, APACHE II, LRINEC, and SOFA scores. **(B)** Receiver operating characteristic curve of the nomogram using 1000 bootstrap resamples. **(C)** Calibration curve of the nomogram using 1000 bootstrap resamples. **(D)** Decision curve analysis of the nomogram.

DCA was conducted to assess the clinical utility of the nomogram. As illustrated in [Figure 4D](#), within the threshold probability range of 0.1 to 0.9, the nomogram yielded a net benefit consistently greater than either the “treat-all” or “treat-none” strategies, suggesting that decisions based on the nomogram would provide clinical benefit within this range. The decision threshold heatmap ([Figure S2](#)) further showed that the model achieved its optimal overall performance within

Table 3 NRI and IDI of the Nomogram Model Compared with SOFA, LRINEC, and APACHE II Scores

Models	NRI			IDI		
	Estimate	95% CI	p-value	Estimate	95% CI	p-value
N-SOFA	0.416	0.226–0.612	<0.001	0.213	0.141–0.286	<0.001
N-LRINEC	0.377	0.174–0.579	<0.001	0.274	0.187–0.361	<0.001
N-APACHE II	0.411	0.228–0.597	<0.001	0.248	0.164–0.332	<0.001

Abbreviations: N, nomogram; NRI, net reclassification improvement; IDI, integrated discrimination improvement; SOFA, Sequential Organ Failure Assessment; APACHE II, Acute Physiology and Chronic Health Evaluation II; LRINEC, Laboratory Risk Indicator for Necrotizing Fasciitis.

the mid-range of decision thresholds (approximately 0.4–0.6). Surgical intervention may be warranted when a patient's predicted risk exceeds this range.

Sensitivity Analysis

Sensitivity analyses were performed by sequentially adjusting for demographic factors and comorbidities. As shown in [Table S1](#), the estimated effect sizes across the original and adjusted models exhibited only minor changes. These findings indicated that the model results are robust.

Discussion

In this study, we developed and internally validated a predictive model for NSTIs among patients with SSTIs. The final model incorporated four independent predictors—age, temperature, depth of infection, and SOFA score—and demonstrated strong discrimination and calibration performance. A nomogram was also constructed to facilitate clinical application, and DCA showed meaningful net clinical benefit within a broad range of threshold probabilities.

Among the identified predictors, SOFA score was an independent risk factor for NSTIs, consistent with recent findings that highlight its prognostic value for mortality and ICU outcomes in severe infections, including NSTIs.^{26,27} However, some studies have suggested that models based on broader clinical characteristics may outperform SOFA or APACHE II scores alone in mortality prediction.²⁸ The SOFA score reflects systemic inflammation and multi-organ dysfunction, which can impair tissue perfusion and immune function, creating a favorable environment for bacterial invasion and tissue necrosis. Early identification of organ dysfunction through the SOFA score may therefore help clinicians intervene earlier and improve outcomes in high-risk patients.

Hypothermia also emerged as a significant predictor of NSTIs in our model. This aligns with previous research showing that hypothermia in septic patients is associated with dysregulated immune responses and increased mortality.²⁹ In the context of severe infections, hypothermia may reflect advanced disease progression, impaired thermoregulation, or systemic inflammatory failure.³⁰ It can also compromise neutrophil function and antimicrobial defense, further promoting pathogen spread and tissue destruction. Therefore, clinicians should regard hypothermia as a potential marker of disease severity and escalate treatment when observed.

Interestingly, our study found that younger age was associated with a higher likelihood of NSTIs, which appears to contrast with the traditional view that older adults are more vulnerable to severe infections.³¹ Nevertheless, this finding is supported by several studies showing that younger patients may have a stronger immune response that paradoxically results in excessive inflammation and tissue damage.³² Additionally, younger individuals may be more likely to engage in activities that result in traumatic injuries or exposure to pathogens, thereby increasing their risk of severe infections.⁹ Previous reports have also shown that young adolescents have a higher incidence of NSTIs.^{33,34} Further research is needed to explore the interplay between immune response dynamics and behavioral factors.

The depth of infection was another strong and clinically intuitive predictor. Deeper infections involving fascia or muscle layers are more prone to necrosis due to reduced perfusion and oxygenation, facilitating anaerobic bacterial growth.⁹ This highlights the importance of timely surgical evaluation and debridement. Prior studies have demonstrated that early surgical intervention (within 6–12 hours of admission) is associated with significantly lower mortality.^{35–37}

Thus, rapid recognition of deep tissue involvement should prompt aggressive surgical management. Surgeons should avoid limiting debridement to superficial or fascial layers and instead extend exploration based on the full clinical picture, especially given the complexity of deep anatomical planes and the difficulty in early diagnosis.

The NSTIs risk prediction nomogram developed in this study demonstrates significant potential for clinical application. Compared with existing scoring systems or models based on CT imaging and microbiological cultures,^{17,18} this model requires fewer variables that are easily obtainable, making it suitable for rapid bedside risk assessment. This enables early identification of NSTIs and supports preoperative emergency decision-making. In the future, the model could be further integrated into electronic medical record (EMR) systems to achieve intelligent alerts.

Nevertheless, this study has several limitations. It was a single-center retrospective study, which may be subject to selection bias. Given the rarity of NSTIs, the available data at our center were limited. Although internal validation was performed using the bootstrap method, external validation in multicenter and prospective cohorts is needed to assess the model's applicability across different healthcare settings. Secondly, the included predictive variables were relatively limited. Future studies may consider incorporating imaging, microbiological, and other biomarker data to develop real-time dynamic prediction models. This would facilitate the early and precise identification of NSTIs, enable refined patient management, and improve clinical outcomes.

Conclusion

We developed and internally validated a clinically applicable nomogram for predicting NSTIs in SSTI patients, incorporating four easily obtainable clinical variables. The model may serve as an adjunct to existing severity scores and has potential for digital integration in triage systems.

Abbreviations

NSTIs, necrotizing soft tissue infections; SSTIs, skin and soft tissue infections; LRINEC, Laboratory Risk Indicator for Necrotizing Fasciitis; SOFA, Sequential Organ Failure Assessment; APACHE II, Acute Physiology and Chronic Health Evaluation II; SD, standard deviation; IQR, interquartile range; OR, odds ratio; CI, confidence interval; LASSO, least absolute shrinkage and selection operator; ROC, receiver operating characteristic; AUC, area under the curve; DCA, decision curve analysis.

Data Sharing Statement

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

Ethics Statement

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Review Committee of the First Affiliated Hospital of Wenzhou Medical University (Approval No. KY2024-R194). A waiver for informed consent was allowed by the ethics review committee in view of the retrospective nature of the research and the anonymity of the data.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Funding

This work was supported by the Key R&D Program Projects of Zhejiang Province (Grant number: 2021C03072).

Disclosure

The authors declare that they have no competing interests.

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