Original Article
Risk factors for postoperative pulmonary infections in non-small cell lung cancer: a regression-based nomogram prediction model

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Abstract: Objective: To identify key risk factors for postoperative pulmonary infections (PPIs) in lung cancer (LC), patients undergoing radical surgery and construct a multiparametric nomogram model to improve PPI risk prediction accuracy, guiding individualized interventions. Methods: A retrospective analysis was conducted on LC patients treated at Yidu Central Hospital of Weifang from March 2020 to May 2023. Among the 1,084 LC cases reviewed, patients were divided into an infected group (n = 131) and an uninfected group (n = 953) based on infection status. Key factors for PPIs were screened using machine learning techniques, including least absolute shrinkage and selection operator (LASSO) regression, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). A nomogram prediction model was developed, and its stability and clinical utility were evaluated using calibration curves and decision curve analysis, with internal validation through random case selection. Results: Thirteen factors - including tumor stage, diabetes history, chronic obstructive pulmonary disease (COPD), operation duration, mechanical ventilation duration, age, C-reactive protein, procalcitonin, high-mobility group box 1, interleukin-6, neutrophil-to-lymphocyte ratio, platelet-to-lymphocyte ratio, and systemic immune-inflammation index - were identified as significantly associated with PPIs. The nomogram model demonstrated high predictive accuracy in internal validation (C-index = 0.935), strong calibration, and substantial clinical benefit. For two randomly selected cases, the model predicted a 63% infection probability for the infected patient and a 32% probability for the uninfected patient, affirming the model's predictive effectiveness. Conclusions: The multiparametric nomogram model developed in this study provides a reliable method for PPI risk prediction in LC patients, supporting clinical decision-making and improving postoperative management.

Keywords: Lung cancer, postoperative pulmonary infection, nomogram model, machine learning

Introduction

Worldwide, lung cancer (LC) ranks among the malignancies with the highest morbidity and mortality rates [1]. In China, LC incidence is also rising, particularly among male cancer patients, where it is the most common malignancy. LC is increasingly prevalent among female patients as well [2, 3]. Characterized by high morbidity and mortality, LC has become a major malignant tumor threatening human health and life [4]. LC's causes are multifactorial; aside from genetic predisposition, smoking is the primary risk factor. Tobacco-derived nitrosamines damage bronchial epithelial cells and activate proto-oncogenes, transforming normal lung cells into cancerous cells [5, 6].

Current treatments for LC include surgery, radiotherapy, chemotherapy, immunotherapy, and traditional Chinese medicine therapies [7, 8]. Surgical resection remains one of the most effective treatments for early- to mid-stage LC, with common procedures including wedge resection, segmentectomy, lobectomy, and pneumonectomy. Of these, lobectomy with compre-

hensive lymph node dissection is the standard radical surgery for LC [9]. Surgical approaches vary based on tumor characteristics and patient tolerance, encompassing extended and local resections. However, despite radical resection, the five-year survival rate post-surgery remains low [10]. Postoperative LC patients frequently experience symptoms such as respiratory restriction, weak cough, and difficulty expectorating due to significant surgical trauma, stimulation to the heart and lungs, and altered chest cavity dynamics [11]. Furthermore, LC patients, often older with compromised immunity and respiratory function, are highly susceptible to infection, making postoperative pulmonary infections (PPIs) a leading cause of mortality [12]. PPIs not only delay recovery and increase hospitalization costs but can also lead to respiratory failure in severe cases [13]. Therefore, identifying risk factors for PPIs after LC resection is essential to reducing their incidence and supporting targeted prevention and treatment.

In current clinical practice, predicting postoperative infections in LC remains challenging. This study aims to improve PPI risk prediction by developing a multiparametric nomogram model that incorporates inflammatory markers, biochemical indices, and clinical parameters. Using machine learning techniques for feature selection and model optimization, this model enhances predictive accuracy. Additionally, the visualized nomogram provides clinicians with intuitive, actionable decision support, facilitating personalized interventions, reducing postoperative infection rates, and enhancing postoperative quality of life in LC patients. This model demonstrates the potential of integrating biomarkers and machine learning in LC management and provides a scientific basis and methodology for future postoperative care in LC.

Materials and methods

Case acquisition

Patient data from LC cases treated at Yidu Central Hospital of Weifang from March 2020 to May 2023 were collected retrospectively. Inclusion criteria: (1) LC diagnosis confirmed by chest computed tomography, bronchoscopy, cytology, or histopathology; (2) Absence of preoperative pulmonary infections; (3) Newly diag-

nosed non-small cell LC, with TNM stage below IIIb [14].

Exclusion criteria: (1) Preoperative pulmonary infection or other infections; (2) Preoperative anti-infection treatments; (3) Incomplete clinical records, referrals, or cases with patient death. Given the study's retrospective design, informed consent was waived with the approval of the Ethics Committee of Yidu Central Hospital of Weifang.

Definition of PPIs

A diagnosis of postoperative pulmonary infection (PPI) requires meeting four out of the following six criteria within one month after surgery: (1) Leukocyte count >15×10^9/L; (2) Body temperature >38°C; (3) Cough and expectoration; (4) Pulmonary rales on auscultation; (5) Infiltrative lung lesions on chest imaging; (6) Positive bacterial culture from deep sputum samples [15].

Case grouping

Of 1,571 cases initially screened based on the inclusion criteria, 487 were excluded based on the exclusion criteria, resulting in 1,084 cases eligible for the study. These patients were grouped by PPI status into an infected group (n = 131) and an uninfected group (n = 953).

Clinical data acquisition

Using outpatient review and electronic medical records, patient information was collected, including age, sex, body mass index (BMI), smoking history, affected lung side, pathological classification, tumor stage, diabetes history, hypertension history, chronic obstructive pulmonary disease (COPD), operation duration, mechanical ventilation time, C-reactive protein (CRP), procalcitonin (PCT), high-mobility group protein B1 (HMGB1), interleukin-6 (IL-6), neutrophil-to-lymphocyte ratio (NLR), platelet-to-lymphocyte ratio (PLR), lymphocyte-to-monocyte ratio (LMR), and systemic immune-inflammation index (SII).

Machine learning models

Least absolute shrinkage and selection operator (LASSO) regression is a penalized regression method that forces some coefficients to

zero, making it highly effective in cases where the number of predictors exceeds the sample size, reducing variables and improving model performance [16].

Support Vector Machine (SVM) is a boundary-based supervised learning algorithm effective for classification and regression. It constructs hyperplanes in high-dimensional space to maximize the margin between classes, making it ideal for binary classification tasks [17].

Extreme Gradient Boosting (XGBoost) is a decision-tree-based ensemble algorithm that improves model performance by optimizing the loss function through gradient boosting and introduces regularization to enhance generalization across datasets [18].

Outcome measures

(1) Identification of differences in baseline data between infected and uninfected groups. (2) Screening of significant PPI factors using LASSO regression, SVM, and XGBoost. (3) Development of a nomogram model based on identified factors, with stability and clinical utility assessed through calibration curves and decision curve analysis (DCA). (4) Evaluation of the model's predictive accuracy in PPI risk using two randomly selected cases.

Statistical analysis

Data preprocessing and initial analysis were conducted using SPSS 26.0. Categorical data were expressed as percentages (%) and analyzed with chi-square tests. For continuous data, the Kolmogorov-Smirnov test assessed data distribution. Normally distributed measurement data were represented as Mean ± SD and analyzed with independent t-tests; non-normally distributed data were presented as median (P25, P75). Further analysis was performed using R (version 4.3.3), employing packages including rms (version 6.4.0), ResourceSelection (version 0.3-5), openxlsx, Matrix, XGBoost, rpart, data.table, ggplot2, kernlab, and pROC. Statistical significance was defined as P<0.05 for all analyses.

Results

Comparison of baseline data

Baseline comparisons showed statistically significant differences in tumor staging, diabetes history, COPD, operation time, duration of mechanical ventilation, age, CRP, PCT, HMGB1, IL-6, NLR, PLR, and SII between infected and uninfected groups (all P<0.05, **Table 1**). No significant differences were observed in other clinical data (all P>0.05).

Classification of measurement data

We employed logistic regression for analysis. Measurement data were adjusted to binary outcomes using receiver operating characteristic (ROC) curve cut-offs to standardize the analysis. ROC curves (**Figure 1**) were plotted, and specificity and sensitivity for each index in predicting PPIs were calculated (**Table 2**).

Screening of characteristic factors of PPIs

Data with significant baseline differences were included and assigned values (**Table 3**). LASSO-Logistic, XGBoost-Logistic, and SVM methods were applied to identify key feature variables, resulting in the selection of 13 significant factors (age, CRP, PCT, HMGB1, IL-6, NLR, PLR, SII, tumor staging, diabetes history, COPD, operation time, and duration of mechanical ventilation). LASSO regression analysis (**Figure 2A**) demonstrated the shrinkage of feature coefficients with increasing regularization (λ), using the minimum criterion and 1-SE rule to identify key predictors. SVM feature selection (**Figure 2B**) showed the error rate variation with feature inclusion, identifying optimal classification features. The XGBoost model's iterative process (**Figure 2C**) used gradient boosting for enhanced feature selection. ROC curves for the models (SVM, XGBoost, and LASSO) revealed high discriminative accuracy, with AUC values exceeding 0.9: 0.945 for SVM, 0.963 for XGBoost, and 0.935 for LASSO, indicating model robustness and reliability of selected variables (**Figure 3**; **Table 4**).

Construction of a nomogram prediction model for PPIs in LC

To enable clinical application, we visualized 13 selected features in a Nomogram model. PCT showed strong correlation with PPIs in LC patients (**Figure 4A**). Calibration curve analysis indicated significant overlap between Apparent and Bias-corrected predictions, closely aligning with the Ideal line, demonstrating good model fit and stability. The model's C-index was 0.935 (0.910-0.960), and the goodness-of-fit test yielded a chi-square value of 11.276 (P =

Table 1. Classification of baseline data

Variables	Infected group (n = 131)	Uninfected group (n = 953)	χ^2/t	P
Sex				
Male	96	677	0.283	0.595
Female	35	276		
Smoking history				
With	76	496	1.646	0.199
Without	55	457		
Affected side				
Left	51	353	0.233	0.89
Right	67	496		
Bilateral	13	104		
Pathological classification				
Adenocarcinoma	103	772	0.42	0.517
Squamous cell carcinoma	28	181		
Tumor staging				
I+II	46	486	11.624	<0.001
III	85	467		
History of diabetes				
With	31	133	8.454	0.004
Without	100	820		
History of hypertension				
With	26	162	0.652	0.419
Without	105	791		
COPD				
With	54	267	9.634	0.002
Without	77	686		
Operation time				
≥3 h	85	457	13.207	<0.001
<3 h	46	496		
Duration of mechanical ventilation				
≥6 h	79	429	10.812	0.001
<6 h	52	524		
Age (years old)	64.37±8.26	58.76±8.06	7.305	<0.001
BMI (kg/m^2)	23.12±1.95	23.03±2.01	0.492	0.623
CRP (mg/L)	61.51±19.12	51.36±14.64	5.843	<0.001
PCT (ng/mL)	2.71 [2.33, 3.27]	1.69 [1.16, 2.23]	11.831	<0.001
HMGB1 (pg/mL)	484.08±120.63	396.64±84.90	8.027	<0.001
IL-6 (pg/mL)	12.66 [9.00, 16.38]	9.37 [6.26, 12.57]	6.656	<0.001
NLR	3.39 [2.29, 4.46]	2.75 [1.69, 3.68]	4.666	<0.001
PLR	131.92±61.12	108.15±41.55	4.316	<0.001
LMR	5.67±1.77	5.51±1.78	1.008	0.315
SII	509.11 [335.30, 694.25]	438.23 [299.97, 576.66]	3.581	<0.001

Note: COPD, chronic obstructive pulmonary disease; BMI, body mass index; CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; LMR, lymphocyte-to-monocyte ratio; SII, systemic immune-inflammation index.

0.186), suggesting no significant evidence to reject good model fit. DCA showed a benefit rate range of 0%-98%, with a peak benefit of 87.91% (**Figure 4B**, **4C**).
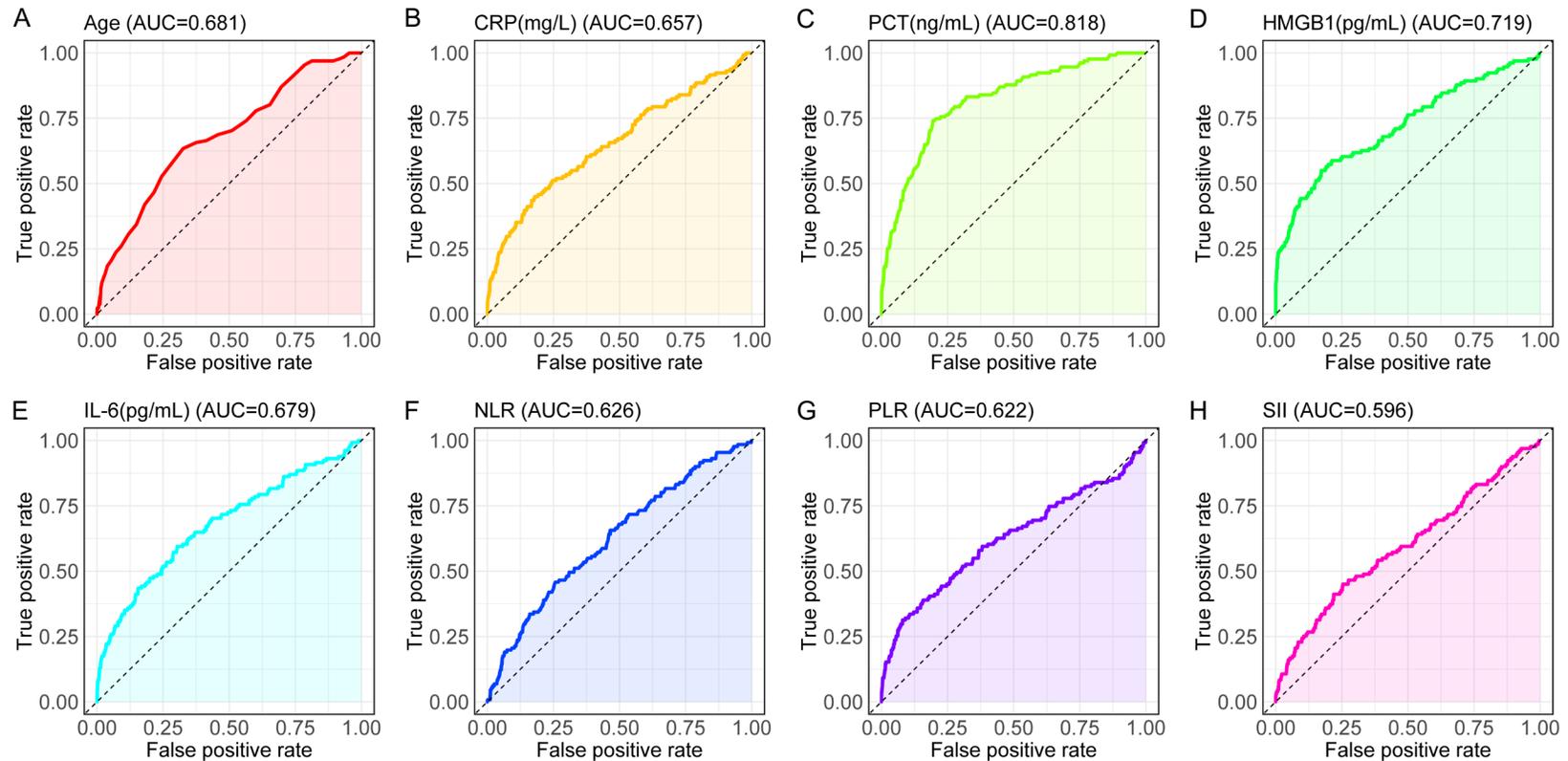
Figure 1. ROC curves of measurement data. A: Age ROC curve, illustrating its discriminative power in prediction. B: CRP (mg/L) ROC curve, assessing its effectiveness in prediction. C: PCT (ng/mL) ROC curve, showing its predictive accuracy. D: HMGB1 (pg/mL) ROC curve, evaluating its performance in prediction. E: IL-6 (pg/mL) ROC curve, indicating its discriminative ability in prediction. F: NLR ROC curve, reflecting its predictive efficacy. G: PLR ROC curve, assessing its capacity for prediction. H: SII ROC curve, displaying its effectiveness in prediction. Note: CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index.

Table 2. ROC curve parameters of measurement data

Marker	AUC	95% CI	Specificity	Sensitivity	Youden index	Cut off
Age	0.681	0.632-0.731	67.47%	63.36%	30.83%	62.5
CRP	0.657	0.602-0.713	82.06%	45.04%	27.09%	64.495
PCT	0.818	0.779-0.858	80.59%	74.05%	54.63%	2.375
HMGB1	0.719	0.667-0.772	82.79%	54.96%	37.75%	476.11
IL-6	0.679	0.626-0.733	69.67%	59.54%	29.22%	11.795
NLR	0.626	0.574-0.677	74.29%	45.80%	20.09%	3.645
PLR	0.622	0.563-0.682	92.03%	31.30%	23.32%	165.395
SII	0.596	0.540-0.652	74.61%	45.04%	19.64%	572.67

Note: ROC, receiver operating characteristic; CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index.

Table 3. Assignment table

Variables	Assignment content
Age	<62.5 = 0, ≥62.5 = 1
CRP	<64.495 = 0, ≥64.495 = 1
PCT	<2.375 = 0, ≥2.375 = 1
HMGB1	<476.11 = 0, ≥476.11 = 1
IL-6	<11.795 = 0, ≥11.795 = 1
NLR	<3.645 = 0, ≥3.645 = 1
PLR	<165.395 = 0, ≥165.395 = 1
SII	<572.67 = 0, ≥572.67 = 1
Tumor staging	I+II = 1, III = 0
History of diabetes	With = 0, without = 1
COPD	With = 0, without = 1
Operation time	≥3 h = 1, <3 h = 0
Duration of mechanical ventilation	≥6 h = 1, <6 h = 0
Infection	With = 1, without = 0

Note: COPD, chronic obstructive pulmonary disease; CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index.

Internal validation of the model

An infected and an uninfected patient were randomly selected to evaluate the model's predictive capability. The Nomogram predicted an infection incidence rate of 63% for the infected patient and 32% for the uninfected patient (**Table 5**).

Discussion

After LC surgery, patients may face a heightened risk of pulmonary infections, often caused by multiple factors that significantly impair respiratory function and elevate postoperative mortality risk [19]. LC predominantly affects middle-aged and elderly patients, whose physi-

cal functions, including immune system performance, naturally decline with age [20]. A range of factors can contribute to the development of pulmonary infections during surgery and the postoperative period, especially in older patients. Variations in infection rates between hospitals may be influenced by physicians' understanding of infection risk factors, patient management approaches, and levels of medical care available [21]. PPIs not only extend recovery time but also increase hospitalization duration and financial costs. Therefore, surgeons must promptly identify and address the potential PPI risk factors that LC patients may encounter after surgery.

In this study, we analyzed 1,084 cases, finding that 131 patients experienced PPIs, with an incidence rate of 12%. In a study by Ding et al. [22], 27 of 244 patients developed PPIs, yielding an incidence rate of 11%. Similarly, Li et al. [23] examined 1,395 patients, reporting a surgical site infection incidence of 13.47% (188/1,395). These findings align closely with ours, suggesting that PPIs are a common concern for patients undergoing LC surgery. We further examined PPI risk factors in LC patients using three machine learning methods. Interestingly, all three methods consistently identified age, CRP, PCT, HMGB1, IL-6, NLR, PLR, SII, tumor staging, diabetes history, COPD, operation time, and duration of mechanical ventilation as independent risk factors for PPIs. For clarity, these factors can be classified into four categories:
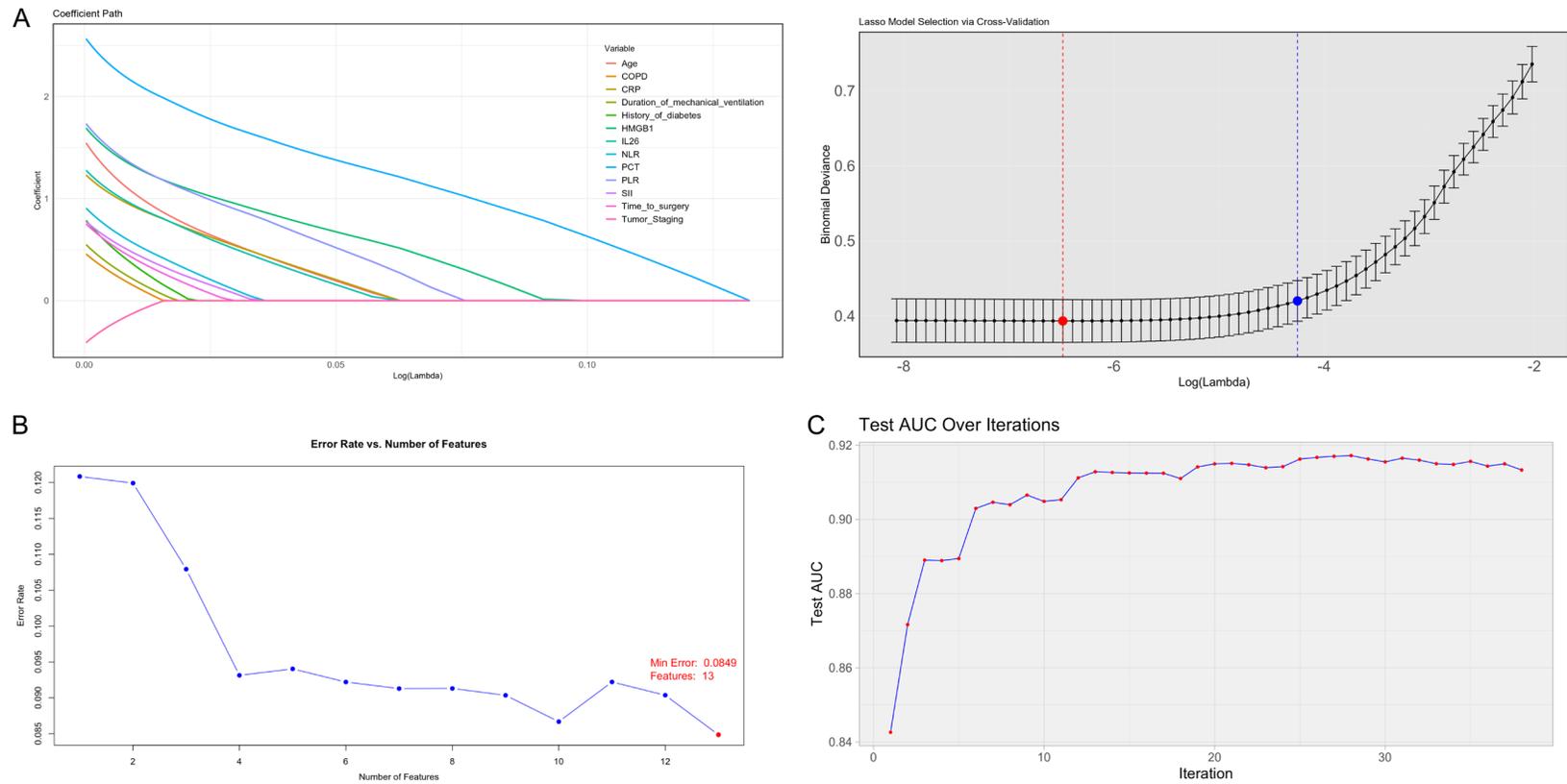
Figure 2. Screening of the characteristic factors of postoperative pulmonary infections using the 3 models. A: LASSO regression regularization and min and 1se. B: The variation of SVM error rate with the number of features. C: XGBoost optimal model iteration path diagram. Note: SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting; LASSO, Least Absolute Shrinkage and Selection Operator.
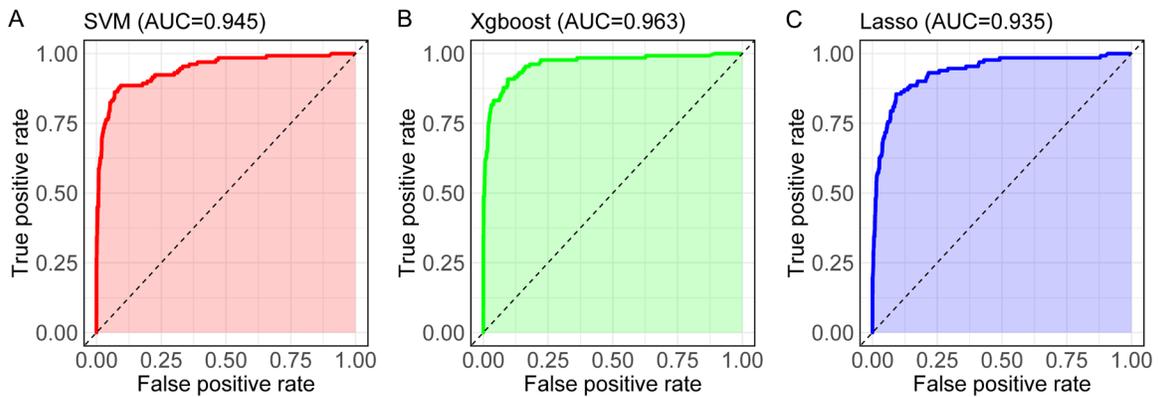
Figure 3. ROC curves of the three machine learning models. A: SVM model ROC curve, demonstrating its classification capability. B: XGBoost model ROC curve, showing its predictive effectiveness. C: Lasso model ROC curve, illustrating its performance in classification. Note: SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting; LASSO, Least Absolute Shrinkage and Selection Operator.

Table 4. Comparison of SVM, XGBoost, and LASSO model performance metrics

Marker	SVM	XGBoost	LASSO
AUC	0.945	0.963	0.935
95% CI	0.922-0.968	0.944-0.982	0.910-0.960
Specificity	92.97%	90.56%	90.87%
Sensitivity	86.26%	90.84%	85.50%
Youden index	79.23%	81.40%	76.37%
Cut off	0.122	0.177	0.169
Accuracy	92.16%	90.59%	90.22%
Precision	86.26%	90.84%	85.50%
F1 Score	72.67%	70.00%	67.88%

Note: SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting; LASSO, Least Absolute Shrinkage and Selection Operator.

patient characteristics, disease characteristics, surgery-related factors, and markers of inflammation and infection.

Among patient characteristics, age is a critical factor influencing PPI risk in non-small cell LC surgery. Elderly patients typically exhibit diminished immune function, lower physiological reserves, and reduced respiratory muscle strength, all of which increase susceptibility to postoperative infections [24]. Additionally, older adults often have multiple chronic conditions, such as diabetes and hypertension, further compromising immune response and reducing the body's ability to manage surgery-induced stress and infections effectively [25]. Furthermore, elderly patients experience slower recovery, with delayed restoration of pulmonary function compared to younger patients, increasing the likelihood of PPIs. Studies have shown that advanced age correlates with higher rates of postoperative complications, such as pneumonia and respiratory failure, significantly impacting recovery and survival outcomes [26]. For example, Zhou et al. [27] found that advanced age substantially increased the probability of postoperative pneumonia in LC patients. Simonsen et al. [28] reported that in super-elderly LC patients (≥80 years), the risk of postoperative pneumonia was 3.64 times higher than in patients under 80.

From the perspective of disease characteristics, tumor staging, diabetes history, and COPD are significant risk factors for postoperative infections in patients with non-small cell lung cancer (NSCLC). Advanced tumor stages often correlate with a higher disease burden and more complex surgeries, which increase postoperative infection risk. Diabetic patients have an elevated susceptibility to infections due to poor glycemic control, compromised immune function, and delayed wound healing [29]. COPD patients, with impaired pulmonary function and reduced respiratory clearance capacity, are prone to sputum retention and pulmonary infections [30]. Additionally, COPD often necessitates prolonged mechanical ventilation, further heightening infection risk. Studies show
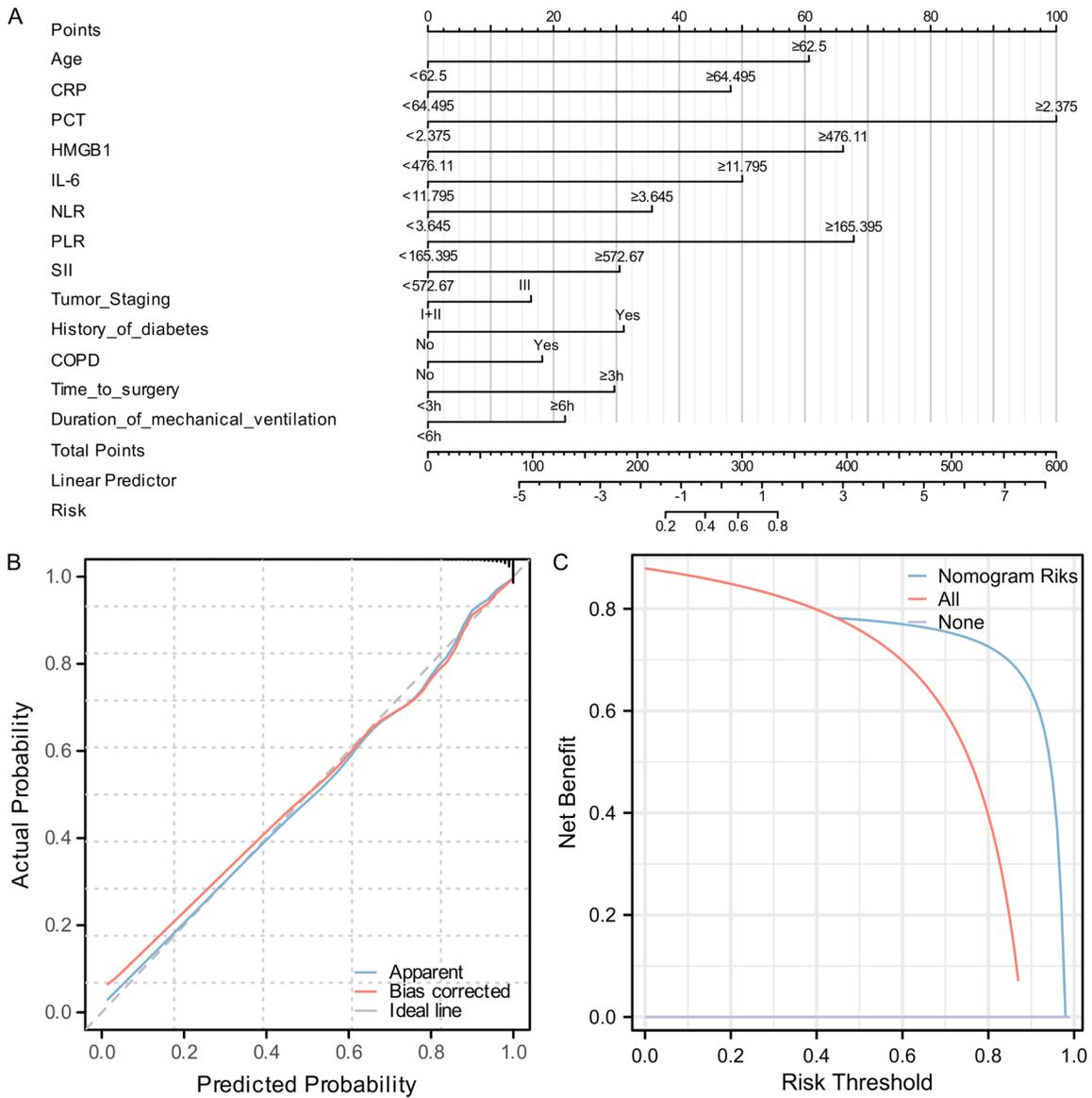
Figure 4. Construction of a nomogram prediction model for postoperative pulmonary infections in lung cancer. A: Nomogram prediction model for postoperative pulmonary infections in lung cancer. B: Stability evaluation of the Nomogram prediction model using calibration curves. C: Evaluation of the clinical benefit rate of the Nomogram prediction model using DCA. Note: CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index.

that pre-existing conditions like these increase the likelihood of PPIs and other complications, adversely affecting recovery and prognosis [31]. A meta-analysis by Zhang et al. [32] confirms that advanced age, diabetes, and lung disease are all significant risk factors for postoperative infections, validating our findings.

Regarding surgery-related characteristics, operation duration and mechanical ventilation time are key factors affecting infection risk after NSCLC surgery. Longer surgeries expose patients to an extended surgical environment and increase infection risk. Prolonged procedures also heighten physiological stress responses and may impair immune function [33]. Similarly, extended mechanical ventilation time increases the likelihood of airway compromise and bacterial invasion, raising the risk of ventilator-associated pneumonia and damag-

Table 5. Information on randomly sampled patients and calculation of incidence

Type	Infected case	Score	Uninfected case	Score
Age	84	61	55	0
CRP	78.34	47.5	80.03	47.5
PCT	2.48	100	1.59	0
HMGB1	409.77	0	365.63	0
IL-6	15.96	50	13.55	50
NLR	5.85	36	4.93	36
PLR	107.61	0	11.12	0
SII	733.65	31	274.1	0
Tumor staging	I+II	0	I+II	0
History of diabetes	No	0	Yes	31
COPD	Yes	28	No	0
Operation time	≥3 h	30	<3 h	0
Duration of mechanical ventilation	<6 h	0	≥6 h	22
Total score	383.5		186.5	
Incidence rate	63%		32%	

Note: COPD, chronic obstructive pulmonary disease; CRP, C-reactive Protein; PCT, procalcitonin; HMGB1, high mobility group box 1; IL-6, interleukin-6; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index.

ing airway mucosa, thus compromising local immunity [34]. Studies indicate that reducing surgery and ventilation times significantly lowers postoperative infection rates [35]. Clinical optimization of surgical and postoperative processes is, therefore, critical in preventing infection. Research by Zeng et al. [36] and Li et al. [23] supports the link between extended operation time and increased nosocomial infection risk in LC patients. Additionally, Wang et al. [37] identified surgical method and duration as independent risk factors for PPIs.

Inflammation and infection markers are also essential in predicting infection risk following NSCLC surgery [38]. Commonly used markers, including CRP, PCT, HMGB1, IL-6, NLR, PLR, and SII, reflect the body's inflammatory and infection status. CRP and PCT are sensitive indicators; their elevated levels often signal bacterial infections post-surgery [39]. Higher levels of HMGB1 and IL-6, both proinflammatory cytokines, correlate with severe inflammatory reactions and increased infection risk [40]. Liu et al. [41] demonstrated that CRP and PCT are useful early predictors for PPIs in cervical cancer patients, and Suberviola's team [42] found that rising PCT levels correlated with higher early infection rates in lung transplant patients. NLR, PLR, and SII provide a comprehensive assessment of immune and inflammatory responses,

aiding in the evaluation of infection risk after surgery [43]. Utilizing these markers together can significantly enhance infection risk prediction accuracy [35, 44], facilitating more individualized intervention strategies and reducing infection rates. For instance, NLR is a key factor in the hospital mortality prediction model for patients with pulmonary infection by Ren et al. [45]. Similarly, Yao et al. [46] reported that NLR, PLR, and SII levels reliably increase in pneumonia patients post-hip fracture surgery.

In the final stage of this study, we developed a multiparametric nomogram model to predict the risk of PPIs in patients with NSCLC. The model achieved a C-index of 0.935, indicating high predictive accuracy. Calibration curve analysis showed strong consistency between actual and predicted outcomes, further confirming the model's stability. Additionally, DCA demonstrated a high clinical benefit rate across a threshold range of 0%-98%, with a maximum benefit rate of 87.91%. This model enables clinicians to assess a patient's risk of pulmonary infections before or shortly after surgery, allowing for timely preventive and therapeutic interventions. For instance, in elderly patients or those with chronic conditions, early identification of elevated infection risk and implementation of rigorous infection control measures - such as enhanced preoperative and postopera-

tive care, shortened operation time, and reduced mechanical ventilation duration - can effectively decrease postoperative infection rates. Moreover, the inclusion of inflammatory and infection markers within the model provides clinicians with valuable reference indicators, supporting more precise and individualized interventions.

While the nomogram model has demonstrated robust predictive performance in internal validation, further external validation and optimization are needed for broader clinical application. Future studies should consider incorporating multicenter data to confirm the model's applicability and reliability across different populations. Additionally, advances in medical technology, including emerging biomarkers and big-data analysis techniques, may further enhance the model's predictive accuracy and clinical value.

In summary, the multiparametric nomogram model developed in this study effectively predicts the risk of postoperative pulmonary infections in LC patients, providing a valuable tool for clinical decision-making and supporting improvements in postoperative management.

Acknowledgements

Disclosure of conflict of interest

None.

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