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ORIGINAL RESEARCH

Construction of a Risk Score Model for Predicting Airway Management in Maxillofacial and Neck Region Space Infections Using Inflammatory Markers

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Purpose: Patients with oral and maxillofacial space infections (OMSI) often experience rapidly progressing disease that can result in acute hypoxia, leading to severe complications such as cerebral hypoxia and cardiac arrest. Effective airway management (intubation or tracheotomy) is crucial in these cases. However, no validated tools currently exist to predict which patients require airway intervention. This study aimed to develop and validate a risk scoring system to predict the need for airway management in patients with OMSI.

Patients and Methods: We conducted a retrospective study of OMSI patients treated between January 2020 and December 2022 and divided them into training and validation cohorts. A risk prediction model was developed using LASSO and logistic regression analyses in the training cohort, and its discrimination and calibration were verified in the validation cohort.

Results: A total of 215 patients (150 for training and 65 for validation) were analyzed. Six independent predictors were identified: dyspnea (OR 3.95, 95% CI 1.38–11.35, $p = 0.011$), BMI (OR 1.14, 95% CI 1.04–1.25, $p = 0.006$), body temperature (OR 2.92, 95% CI 1.34–6.37, $p = 0.007$), sIL-2R level (OR 1.01, 95% CI 1.01–1.01, $p = 0.007$), CRP level (OR 1.01, 95% CI 1.01–1.01, $p = 0.047$), and retropharyngeal space involvement (OR 15.71, 95% CI 3.36–73.40, $p < 0.001$). Internal validation revealed good discrimination (AUC 0.91) and calibration (HL test, $p = 0.061$), with similar performance in the validation cohort (AUC 0.86; HL test, $p = 0.133$). Decision curve analysis demonstrated clinical utility in both cohorts.

Conclusion: The proposed risk scoring system reliably predicts the need for airway management in OMSI patients, which enables clinicians to identify high-risk patients early and implement preventive strategies to improve outcomes.

Keywords: oral and maxillofacial space infections, risk scoring system, predictive modeling, clinical decision-making

Introduction

Oral and maxillofacial space infections (OMSI) represent a considerable and growing clinical burden, accounting for more than 144,000 surgical procedures in Germany alone (2005–2022), with standardized incidence rates increasing from 45.7% to 11.1/100,000 person-years by 2022. This pathological process, typically originating from odontogenic (68.4%), pharyngeal, or traumatic sources, disproportionately affects men (57.2%) and patients older than 35 years, particularly octogenarians, whose incidence has increased by 120.5%.[1] Mirroring this trend, England presented a 3.58-fold increase in severe dental abscess admissions from 2000–2020, which increased from 1.71 to 5.36/100,000 population, with

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corresponding bed-day use rate tripling.[2] Crucially, the anatomic proximity of fascial spaces to vital structures facilitates rapid spread to mediastinal and intracranial compartments,[3,4] leading to severe complications such as Ludwig's angina, mediastinal infections,[5] intracranial infections,[6,7] sepsis, and even death. Airway obstruction and subsequent respiratory distress are among the most common and serious consequences of OMSI.[8]

Given that airway compromise is the most lethal complication of OMSI, its effective management is paramount. Early identification of patients who may need airway intervention is essential, as prompt action can substantially reduce mortality and complications and prevent outcomes such as respiratory distress, acute cerebral hypoxia, and cardiac arrest.[9] While significant advances have been made in the diagnosis and treatment of OMSI, predictive studies specifically focused on airway management remain scarce.[10–12] Moreover, conventional airway assessment tools, such as the Mallampati score and the LEMON criteria, are designed primarily to predict the difficulty of intubation in elective settings, not the impending need for airway intervention due to a dynamic pathological process.[13,14] These static anatomical assessments often fail to capture the rapidly progressing edema, trismus, and tissue distortion characteristic of OMSI, which can lead to sudden and catastrophic airway collapse. This mismatch between static assessments and a dynamic disease process makes early assessment at admission both critical and exceptionally difficult and often necessitates urgent and complex multidisciplinary collaboration.

To address these specific shortcomings and fill this critical gap, the aim of this study was to develop and validate a novel, reliable risk scoring system specifically designed for patients with OMSI. Our objective was to develop a practical tool that integrates crucial clinical signs, key radiological findings, and advanced inflammatory biomarkers to provide a more accurate and objective prediction of the need for airway management. Such a system is expected to become a standardized tool that enhances patient safety and care efficiency by guiding timely and appropriate airway management decisions, ultimately reducing complications and driving innovation in the treatment of these severe infections.

Materials and Methods

Study Design and Patient Selection

This retrospective cohort study was conducted at Shanghai Ninth People's Hospital and approved by the institutional review board (Approval No. SH9H-2024-T155-1). We identified 215 patients who were diagnosed with oral and maxillofacial space infections (OMSI) between August 2020 and September 2022. The requirement for informed consent was waived because of the study's retrospective nature and the use of fully anonymized data.

The diagnosis of OMSI was confirmed on the basis of a combination of clinical and radiological findings according to the following criteria: (1) the presence of a diffuse inflammatory process within the potential spaces and fascial planes of the maxillofacial and neck regions and (2) the support of evidence from contrast-enhanced computed tomography (CT) demonstrating abscess formation or cellulitis. This study included patients with severe infections of the oral, maxillofacial, and neck regions originating from various sources, with a predominance of odontogenic origins but also including glandular, hematogenous, and iatrogenic causes.

For statistical analysis, the primary regions of infection identified on imaging were classified into one of three major anatomical categories: the suprahyoid region, the infrahyoid region, and the retropharyngeal region. The suprahyoid region was defined as any infection involving one or more spaces located predominantly superior to the hyoid bone, encompassing the submandibular, sublingual, submental, buccal, masticatory (masseteric, pterygoid, and temporal), parotid, and canine fossa spaces. The infrahyoid region included infections involving primarily spaces inferior to the hyoid bone, such as the pretracheal space. Owing to its critical role as a major pathway for mediastinal spread, the retropharyngeal region was analyzed as a distinct category.

A total of 215 patients were ultimately included after the following inclusion criteria were applied: (1) diagnosis of OMSI (as defined above) and treatment at Shanghai Ninth People's Hospital; (2) availability of laboratory tests and maxillofacial-neck CT imaging; and (3) complete documentation of disease progression and clinical examinations.

The exclusion criteria were as follows: (1) infections secondary to benign or malignant tumors; (2) a history of chemoradiotherapy to the head and neck region; (3) an unwillingness to accept or undergo active treatment at our institution; and (4) records with significant missing data for key predictive variables.

Definitions and Grouping of Outcomes

The primary outcome of this study was the need for airway management, defined as the need for either endotracheal intubation or tracheotomy at any point during hospitalization due to airway compromise. On the basis of this outcome, patients were divided into two groups for analysis: the airway management group and the non-airway management group. Notably, this grouping was determined by the naturally occurring clinical course of each patient and was not an allocation decision made by the researchers.

Data Collection

Data were collected by two experienced clinicians. All the predictor variables included in the analysis were collected from the initial assessments performed upon patient admission or within the first 24 hours and, critically, prior to the decision for any major intervention, such as endotracheal intubation or tracheotomy. Potential predictive variables included the following patient characteristics: demographic predictors, medical history, clinical signs and symptoms, imaging results, and laboratory findings. The demographic predictors included age, sex, and disease duration (from the time of symptom onset to the time of hospital visit). Medical history included diabetes mellitus, hypertension, heart disease and other comorbidities. Clinical signs and symptoms recorded included body temperature, body mass index (BMI), heart rate, pain, trismus, dyspnea, and dysphagia. Imaging assessments included the primary regions of infection, gas formation, and multispace involvement. On the basis of a review of the literature, we categorized the primary infection sites of OMSI into three anatomical regions: the suprahyoid, infrahyoid, and retropharyngeal regions.[15] The following laboratory findings have been previously reported to be associated with a poor prognosis in patients with OMSI: white blood cell count (WBC); lymphocyte percentage (LY%); neutrophil percentage (NEUT%); blood glucose level; and the levels of inflammatory markers such as C-reactive protein (CRP),[16,17] sIL-2R, interleukin-6 (IL-6),[18] IL-8, IL-10, and tumor necrosis factor-alpha (TNF-α). Variables for which >5% of the data were missing were excluded from the analysis.

Statistical Analysis

Continuous variables are presented as medians and interquartile ranges (IQRs), whereas categorical variables are presented as frequencies and percentages (%). Univariate analyses were conducted using the Mann–Whitney *U*-test, chi-square test, and Fisher's exact test. The patients were randomly assigned to training and validation cohorts at a 7:3 ratio using R software. Logistic regression analysis was performed to identify statistically significant influencing factors. Multivariate logistic regression included factors for which P was < 0.05 from the univariate analysis and revealed significant variables ($P < 0.05$) influencing the outcome. Least absolute shrinkage and selection operator (LASSO) regression was applied to minimize potential collinearity of variables measured from the same patient. Variables identified by LASSO regression were further analyzed using a logistic regression model, and a clinical risk score nomogram was constructed within the training cohort to visualize the model. The odds ratio (OR) and 95% confidence interval (CI) were calculated by the model, and the final retained variables were used as predictors.

To evaluate the discriminative performance of the risk score, the area under the curve (AUC) of the receiver operating characteristic (ROC) curve was measured. A calibration curve was plotted alongside the Hosmer–Lemeshow (HL) test to assess calibration, where the results of a nonsignificant HL test statistic indicated good calibration. Moreover, decision curve analysis (DCA) was performed to evaluate the clinical usefulness of the generated risk score by assessing the net benefits at various threshold probabilities in the training cohort. The risk score developed in the training cohort was then further validated in the validation cohort. The performance of the risk score in terms of discrimination, calibration, and DCA was assessed in the validation cohort using the same methods described above. Statistical significance was set at $p < 0.05$ for all analyses. Statistical analyses were performed using SPSS version 26.0 software and the R environment, version 4.4.0 (R Foundation for Statistical Computing, Vienna, Austria).

To control for confounding variables, this study employed both multivariate logistic regression and least absolute shrinkage and selection operator (LASSO) regression. This multivariable approach serves as the statistical "internal control" by adjusting for the potential confounding effects of various patient characteristics, thus isolating the independent impact of each predictor.

Results

Characteristics of Patients in the Training and Validation Cohorts

The overall flow chart of patient selection is shown in Figure 1. In total, 215 patients were included in this study and randomly assigned to training (n=150) or validation (n=65) cohorts at a 7:3 ratio using R software. The training cohort included 150 patients, while the validation cohort included 65 patients. Baseline characteristics were generally comparable between the two cohorts, with detailed information presented in Table 1.

Characteristics of the Training Cohort

In the training cohort, 41 of 150 patients required airway management. The median age was 55 years (IQR 43–68 years), and the median BMI was 23.14 (IQR 21.30–25.22). Among these patients, 102 (68%) were men. In the training cohort, 31 patients (20.7%) were diagnosed with diabetes, and 51 patients (34.0%) had hypertension. The most involved infection site was the suprahyoid region, followed by the infrahyoid and retropharyngeal regions. Contrast-enhanced or maxillofacial CT scans revealed multispace involvement in 91 patients (60.7%) and gas formation in 39 patients (26.0%). The other clinical characteristics of the training cohort are summarized in Table 2. To further assess the need for airway management, patients were divided into two groups: an airway management group and a non-airway management group. In the non-airway management group, 85 patients (78.0%) underwent drainage of the infection site under local anesthesia, while 24 patients (22.0%) required general anesthesia for surgical drainage. In the airway management group, 39 patients (95.1%) were extubated more than 24 hours post-surgery, one patient (2.4%) required prolonged airway management through endotracheal intubation or tracheostomy because of respiratory distress, and one patient experienced a fatal outcome. This single fatality, due to septic shock, resulted in an overall mortality rate of 0.7% (1/150).

Variable Selection and Nomogram Construction

A total of 38 variables, including basic patient characteristics, laboratory test results, symptoms, and medical history, were collected from each patient in the training cohort. After univariate analysis, variables without statistically significant differences were excluded (Table 2). To prevent overfitting and address potential multicollinearity, 23 independent variables were selected for LASSO regression analysis, with airway management used as the outcome variable

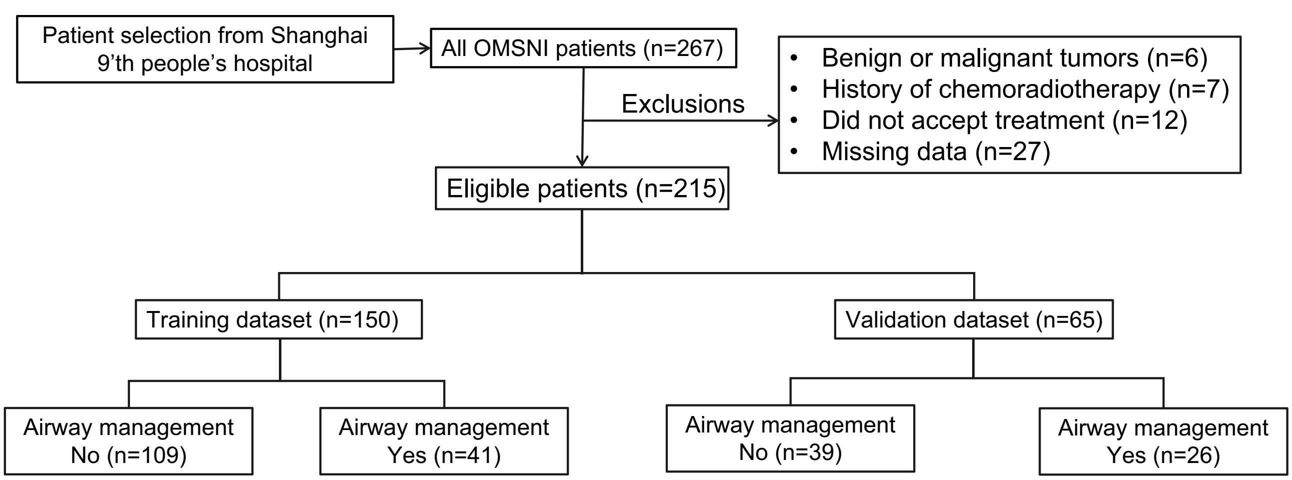

Figure 1 Flowchart illustrating patient selection and grouping process.
Abbreviation: OMSI, oral and maxillofacial space infections.

Table 1 Baseline Characteristics of Patients and Cohort Grouping Information

Characteristics	Total Cohort (n = 215)	Validation Cohort (n = 65)	Training Cohort (n = 150)	P
Age, median (IQR), years	55.00 (39.00, 67.50)	52.00 (35.00, 65.00)	55.00 (43.00, 68.00)	0.166
BMI, median (IQR)	23.44 (21.30, 25.45)	23.67 (21.45, 25.78)	23.14 (21.30, 25.22)	0.397
Sex, male, n (%)	147 (68.37)	45 (69.23)	102 (68.00)	0.859
Body temperature, median (IQR), °C	36.50 (36.40, 37.00)	36.50 (36.40, 37.00)	36.50 (36.40, 37.00)	0.770
Heart rate, median (IQR), bpm	86.00 (78.00, 100.00)	87.00 (78.00, 100.00)	86.00 (78.00, 100.00)	0.937
Disease duration, median (IQR), days	7.00 (6.00, 14.00)	7.00 (6.00, 14.00)	7.50 (6.00, 14.00)	0.959
Hypertension, n(%)	68 (31.63)	17 (26.15)	51 (34.00)	0.084
Heart attack, n(%)	17 (7.91)	2 (3.08)	15 (10.00)	0.084
Diabetes mellitus, n(%)	42 (19.53)	24 (16.22)	18 (26.87)	0.068
Multispace involvement, n (%)	134 (62.33)	43 (66.15)	91 (60.67)	0.446
Odynophagia, n(%)	157 (74.76)	52 (81.25)	105 (71.92)	0.152
Dyspnea, n(%)	73 (34.76)	28 (43.75)	45 (30.82)	0.070
Gas formation, n(%)	56 (26.05)	17 (26.15)	39 (26.00)	0.981
Pain, n(%)				0.851
0	19 (8.88)	5 (7.69)	14 (9.40)	
1	39 (18.22)	10 (15.38)	29 (19.46)	
2	61 (28.50)	20 (30.77)	41 (27.52)	
3	95 (44.39)	30 (46.15)	65 (43.62)	
Trismus, n (%)				0.195
0	55 (25.70)	19 (29.23)	36 (24.16)	
1	25 (11.68)	3 (4.62)	22 (14.77)	
2	54 (25.23)	18 (27.69)	36 (24.16)	
3	80 (37.38)	25 (38.46)	55 (36.91)	
Laboratory test				
WBC, median (IQR), 10^9/L	14.06 (11.17, 17.55)	14.38 (11.94, 17.54)	13.94 (10.49, 17.55)	0.311
NEUT, median (IQR), %	83.40 (76.95, 89.65)	83.30 (78.80, 88.90)	83.45 (75.73, 89.85)	0.745
LY, median (IQR), %	8.00 (4.65, 14.50)	7.60 (5.30, 13.00)	8.15 (4.30, 15.25)	0.970
CRP, median (IQR), mg/L	73.83 (34.59, 156.88)	74.56 (45.49, 160.00)	73.74 (34.59, 152.86)	0.675
sIL-2R, median (IQR), U/mL	542.00 (371.50, 944.50)	476.00 (361.00, 940.00)	559.50 (378.25, 949.00)	0.260
IL-6, median (IQR), pg/mL	16.20 (8.49, 38.70)	15.90 (7.87, 40.57)	17.90 (9.27, 37.62)	0.911
IL-8, median (IQR), pg/mL	9.15 (5.95, 16.30)	9.27 (6.48, 17.30)	9.14 (5.74, 15.45)	0.625

(*Continued*)

Table 1 (Continued).

Characteristics	Total Cohort (n = 215)	Validation Cohort (n = 65)	Training Cohort (n = 150)	P
IL-1β, median (IQR), pg/mL	4.66 (2.67, 10.65)	5.57 (2.91, 11.20)	4.53 (2.64, 10.38)	0.296
IL-10, median (IQR), pg/mL	4.04 (2.23, 7.06)	4.63 (2.35, 7.00)	3.79 (2.17, 7.06)	0.643
TNF-α, median (IQR), pg/mL	8.22 (5.38, 14.50)	8.61 (4.88, 14.90)	7.92 (5.53, 14.05)	0.851
PCT, median (IQR), ng/mL	0.12 (0.08, 0.52)	0.16 (0.08, 0.97)	0.11 (0.08, 0.34)	0.252
AST, median (IQR), U/L	18.00 (13.00, 24.00)	17.00 (14.00, 26.00)	18.00 (13.00, 23.75)	0.678
ALT, median (IQR), U/L	21.00 (16.00, 37.50)	23.00 (17.00, 39.00)	20.00 (15.25, 37.00)	0.262
PT, median (IQR), s	12.20 (11.50, 13.00)	12.00 (11.30, 12.80)	12.20 (11.60, 13.15)	0.242
APTT, median (IQR), s	26.20 (23.85, 28.40)	26.00 (23.20, 27.60)	26.50 (24.02, 28.65)	0.178
Fibrinogen, median (IQR), g/L	5.44 (4.40, 7.00)	5.81 (4.63, 6.88)	5.17 (4.27, 7.05)	0.129
D-Dimer, median (IQR), mg/L	0.93 (0.51, 1.77)	0.98 (0.49, 2.07)	0.93 (0.52, 1.72)	0.724
Blood glucose, median (IQR), mmol/L	7.50 (6.20, 10.20)	7.70 (6.30, 11.20)	7.45 (6.20, 10.15)	0.633
Primary regions of infection				
Suprahyoid region, n(%)	86 (40.00)	23 (35.38)	63 (42.00)	0.363
Infrahyoid region, n(%)	98 (45.58)	31 (47.69)	67 (44.67)	0.682
Retropharyngeal region, n(%)	31 (14.42)	11 (16.92)	20 (13.33)	0.491

Abbreviations: ALT, alanine aminotransferase; APTT, activated partial thromboplastin time; AST, aspartate aminotransferase; BMI, Body Mass Index; bpm, beats per minute; CRP, C-reactive protein; IL-1β, Interleukin-1 beta; IL-6, Interleukin-6; IL-8, Interleukin-8; IL-10, Interleukin-10; IQR, interquartile range; LY, lymphocyte; n, number; NEUT, neutrophil; PCT, procalcitonin; PT, prothrombin time; s, seconds; sIL-2R, soluble Interleukin-2 receptor; TNF-α, tumor necrosis factor-α; WBC, white blood cell.

Table 2 Demographic and Clinical Characteristics of Patients with OMSI in the Training Cohort

Predictors	All (n=150)	Airway Management		P
		No (n=109)	Yes (n=41)	
Age, median (IQR), years	55.00 (43.00, 68.00)	54.00 (39.00, 65.00)	59.00 (53.00, 71.00)	**0.014**
BMI, median (IQR),	23.14 (21.30, 25.22)	22.79 (21.09, 24.84)	23.66 (22.09, 27.55)	**0.036**
Sex, male, n(%)	102 (68.00)	78 (71.56)	24 (58.54)	0.128
Body temperature, median (IQR), C	36.50 (36.40, 37.00)	36.50 (36.30, 36.70)	37.00 (36.50, 37.20)	**<0.001**
Heart rate, median (IQR), bpm	86.00 (78.00, 100.00)	88 (77, 101)	85 (78, 96)	0.563
Disease duration, median (IQR), days	7.50 (6.00, 14.00)	8.00 (6.00, 14.00)	7.00 (6.00, 12.00)	0.437
Hypertension, n(%)	51 (34.00)	32 (29.36)	19 (46.34)	**0.050**
Heart attack, n(%)	15 (10.00)	10 (9.17)	5 (12.20)	0.807
Diabetes mellitus, n(%)	31 (20.67)	20 (18.35)	11 (26.83)	0.253
Multispace involvement, n (%)	91 (60.67)	55 (50.46)	36 (87.80)	**<0.001**

(*Continued*)

Table 2 (Continued).

Predictors	All (n=150)	Airway Management		P
		No (n=109)	Yes (n=41)	
Odynophagia, n(%)	107 (71.33)	74 (67.89)	33 (80.49)	0.128
Dyspnea, n(%)	47 (31.33)	23 (21.10)	24 (58.54)	**<0.001**
Gas formation, n (%)	39 (26.00)	22 (20.18)	17 (41.46)	**0.008**
Pain, n (%)				**<0.001**
0	14 (9.33)	12 (11.01)	2 (4.88)	
1	29 (19.33)	27 (24.77)	2 (4.88)	
2	42 (28.00)	37 (33.94)	5 (12.20)	
3	65 (43.33)	33 (30.28)	32 (78.05)	
Trismus, n (%)				0.878
0	36 (24.00)	27 (24.77)	9 (21.95)	
1	22 (14.67)	16 (14.68)	6 (14.63)	
2	37 (24.67)	25 (22.94)	12 (29.27)	
3	55 (36.67)	41 (37.61)	14 (34.15)	
Laboratory test				
WBC, median (IQR), 10^9/L	13.94 (10.49, 17.55)	13.10 (10.34, 17.04)	14.89 (11.10, 18.95)	0.207
NEUT, median (IQR), %	83.45 (75.73, 89.85)	83.00 (73.60, 88.20)	88.30 (77.70, 92.20)	**0.006**
LY, median (IQR), %	8.15 (4.30, 15.25)	10.00 (5.40, 16.70)	5.00 (3.10, 10.20)	**0.002**
CRP, median (IQR), mg/L	73.74 (34.59, 152.86)	59.36 (28.34, 103.45)	140.23 (72.37, 217.78)	**<0.001**
sIL-2R, median (IQR), U/mL	559.50 (378.25, 949.00)	501.00 (336.00, 667.00)	1006.00 (588.00, 1744.00)	**<0.001**
IL-6, median (IQR), pg/mL	17.90 (9.27, 37.62)	15.70 (7.46, 31.90)	26.70 (12.64, 94.30)	**0.025**
IL-8, median (IQR), pg/mL	9.14 (5.74, 15.45)	8.12 (5.23, 12.50)	14.60 (8.13, 27.60)	**<0.001**
IL-1β, median (IQR), pg/mL	4.53 (2.64, 10.38)	3.89 (2.53, 8.79)	7.37 (2.71, 11.50)	0.117
IL-10, median (IQR), pg/mL	3.79 (2.17, 7.06)	3.54 (2.15, 7.06)	4.23 (2.84, 7.06)	0.584
TNF-α, median (IQR), pg/mL	7.92 (5.53, 14.05)	7.01 (5.20, 10.60)	14.20 (7.33, 18.60)	**<0.001**
PCT, median (IQR), ng/mL	0.11 (0.08, 0.34)	0.10 (0.06, 0.20)	0.25 (0.10, 3.07)	**<0.001**
AST, median (IQR), U/L	18.00 (13.00, 23.75)	17.00 (13.00, 23.00)	20.00 (14.00, 36.00)	0.068
ALT, median (IQR), U/L	20.00 (15.25, 37.00)	21.00 (16.00, 37.00)	19.00 (11.00, 37.00)	0.494
PT, median (IQR), s	12.20 (11.60, 13.15)	12.00 (11.30, 12.70)	13.40 (12.50, 14.10)	**<0.001**
APTT, median (IQR), s	26.50 (24.02, 28.65)	26.50 (24.30, 28.40)	26.80 (23.70, 29.40)	0.537
Fibrinogen, median (IQR), g/L	5.17 (4.27, 7.05)	5.02 (4.26, 6.57)	6.37 (4.40, 7.55)	0.114
D-Dimer, median (IQR), mg/L	0.93 (0.52, 1.72)	0.76 (0.46, 1.29)	1.38 (0.74, 2.44)	**<0.001**
Blood glucose, median (IQR), mmol/L	7.45 (6.20, 10.15)	7.00 (6.00, 9.50)	8.40 (7.40, 11.30)	**0.010**

(*Continued*)

Table 2 (Continued).

Predictors	All (n=150)	Airway Management		P
		No (n=109)	Yes (n=41)	
Primary regions of infection				
Suprahyoid region, n(%)	63 (42.00)	59 (54.13)	4 (9.76)	**<0.001**
Infrahyoid region, n(%)	67 (44.67)	47 (43.12)	20 (48.78)	0.534
Retropharyngeal region, n(%)	20 (13.33)	3 (2.75)	17 (41.46)	**<0.001**

Note: Bold text indicates statistical significance (p < 0.05).
Abbreviations: ALT, alanine aminotransferase; APTT, activated partial thromboplastin time; AST, aspartate aminotransferase; BMI, Body Mass Index; bpm, beats per minute; CRP, C-reactive protein; IL-1β, Interleukin-1 beta; IL-6, Interleukin-6; IL-8, Interleukin-8; IL-10, Interleukin-10; IQR, interquartile range; LY, lymphocyte; n, number; NEUT, neutrophil; PCT, procalcitonin; PT, prothrombin time; s, seconds; sIL-2R, soluble Interleukin-2 receptor; TNF-α, tumor necrosis factor-α; WBC, white blood cell.

(Figure 2a). LASSO regression analysis revealed that at the optimal λ value of 0.069 (Figure 2b), eight features were significantly associated with airway management: BMI, body temperature, dyspnea, retropharyngeal infection, gas formation, pain, CRP, and sIL-2R. These variables included BMI, body temperature, dyspnea status, retropharyngeal infection, gas formation, pain, CRP level, and sIL-2R level. To control for factor effects, the eight variables with $p < 0.05$ were subsequently included in a multivariate logistic regression. This analysis revealed statistically significant predictors: dyspnea at admission (OR 3.95, 95% CI 1.38–11.35; P = 0.011), BMI (OR 1.14, 95% CI 1.04–1.25; P = 0.011), body temperature (OR 2.92, 95% CI 1.34–6.37; P = 0.007), sIL-2R level (OR 1.01, 95% CI 1.01–1.01; P = 0.007), CRP level (OR 1.01, 95% CI 1.01–1.01; P = 0.047), and retropharyngeal infection (OR 15.71, 95% CI 3.36–73.40; P < 0.001) (Table 3). On the basis of the results of the LASSO and multivariate logistic regression analyses, along with clinical outcomes, six factors for OMSI risk prediction were identified and incorporated into a nomogram (Figure 3).

In the internal validation cohort, the ROC curves demonstrated that the risk score had good discriminatory ability, with an AUC of 0.91 (95% CI: 0.86–0.96) in the training cohort and 0.86 (95% CI: 0.76–0.95) in the validation cohort (Figure 4a and b), indicating excellent discrimination of the nomogram. The Hosmer–Lemeshow (HL) goodness-of-fit test results yielded P values of 0.061 for the training cohort and 0.133 for the validation cohort, suggesting good model calibration. In both cohorts, all the predicted probabilities closely aligned with the 45° reference line on the calibration plots (Figure 4c and d), demonstrating good agreement between the actual and predicted outcomes of the nomogram. Decision curve analysis (DCA) was performed to evaluate the clinical utility and potential benefit of the OMSI airway

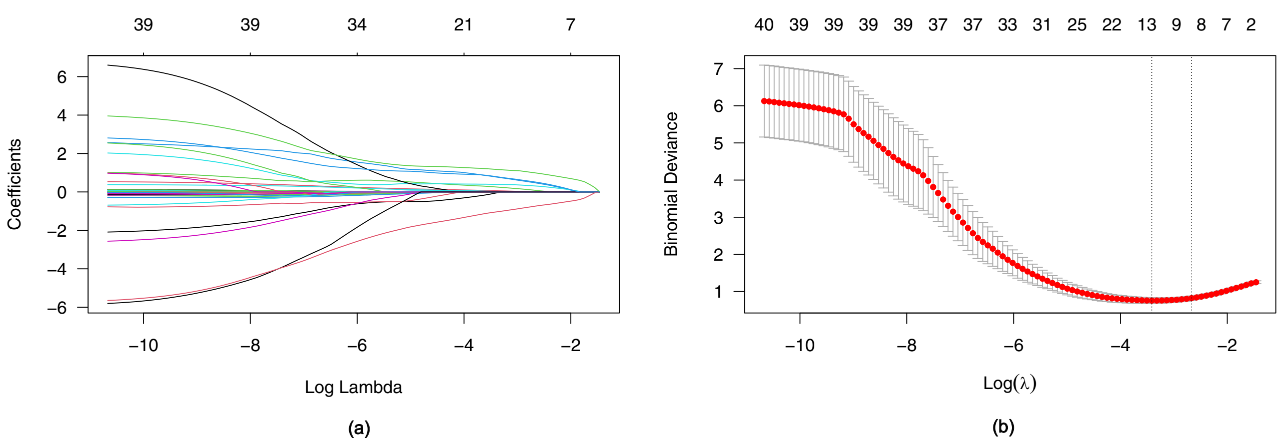

Figure 2 LASSO regression analysis to select characteristic factors. (**a**) 10-fold cross-validation to draw vertical lines at selected values, where the optimal lambda produces nine nonzero coefficients. (**b**) The coefficient profiles of 38 texture variables were plotted from the log(λ) sequence in the LASSO model. Vertical dotted lines indicate the minimum mean square error (λ = 0.032) and the standard error of the minimum distance (λ = 0.069).

Table 3 Multivariate Analysis of Predictors for Airway Management in Patients with OMSI in the Training Cohort

Characteristics	Univariate Analysis		Multivariate Analysis	
	OR (95% CI)	**P**	**OR (95% CI)**	**P**
Dyspnea				
0	1.00 (Reference)		1.00 (Reference)	
1	5.28 (2.44~11.44)	**<0.001**	3.95 (1.38~11.35)	**0.011**
BMI	1.09 (1.01~1.17)	**0.022**	1.14 (1.04~1.25)	**0.006**
Body temperature	3.64 (1.74~7.65)	**<0.001**	2.92 (1.34~6.37)	**0.007**
sIL-2R	1.01 (1.01~1.01)	**<0.001**	1.01 (1.01~1.01)	**0.007**
CRP	1.01 (1.01~1.01)	**<0.001**	1.01 (1.01~1.01)	**0.047**
Retropharyngeal				
No	1.00 (Reference)			
Yes	25.03 (6.79~92.29)	**<0.001**	15.71 (3.36~73.40)	**<0.001**
Gas formation				
No	1.00 (Reference)			
Yes	2.80 (1.29~6.10)	**0.009**		
Pain				
0	1.00 (Reference)			
1	0.44 (0.05~3.54)	0.444		
2	0.81 (0.14~4.73)	0.816		
3	5.82 (1.21~28.08)	**0.028**		

Notes: Bold text indicates statistical significance ($p < 0.05$). The "Reference" category serves as the baseline for comparison in the odds ratio calculation.
Abbreviations: BMI, Body Mass Index; CI, confidence interval; CRP, C-reactive protein; OR, odds ratio; sIL-2R, soluble Interleukin-2 receptor.

management prediction model. In the DCA curve, the x-axis represents the threshold probability, and the y-axis indicates the net benefit. In the validation cohort of this study, the DCA curve revealed greater net benefits (Figure 4e and f). The model showed a greater net benefit than both the "manage all" and "manage none" strategies across most threshold ranges. This finding indicates that the model has strong clinical utility, particularly within threshold between 0.2 and 0.6, providing greater net benefits than alternative strategies do.

These findings confirm that the model maintained strong predictive performance and clinical utility within the validation cohort. Overall, compared with the "manage all" and "manage none" strategies, the prediction model yielded greater net benefits across most threshold ranges, underscoring its potential to assist clinicians in making informed airway management decisions. These findings further support the model's significant clinical utility, particularly in assisting physicians in deciding whether to perform airway management on OMSI patients. Furthermore, the nomogram developed in this study performed well and demonstrated strong predictive ability.

Discussion

In this study, we used univariate logistic regression, LASSO, and multivariate logistic regression to develop and validate a clinical risk score to predict the need for airway management in patients with oral and maxillofacial space infection

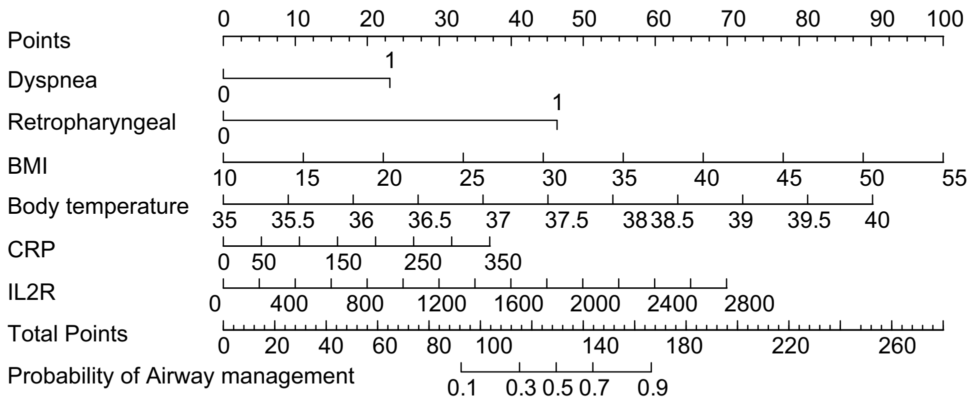

Figure 3 Nomogram for predicting the risk of airway management requirement in patients with OMSI. To predict the risk of airway management requirement using the logistic regression model, the following procedure was applied: first, for each predictor, a vertical line was drawn to the "Points" axis to determine its associated score. These scores were then summed to obtain a total score. Subsequently, a second vertical line was drawn from the "Total Points" axis downward to the "Risk" axis, where the corresponding value represented the predicted probability of requiring airway management.

(OMSI). The model incorporates six clinically accessible variables—dyspnea, BMI, body temperature, sIL-2R level, CRP level, and primary infection site—into a single, quantifiable tool. Although these predictors are individually recognized in clinical practice, the principal contribution of this work lies in their integration into a standardized instrument that may support decision-making beyond subjective assessment alone.[19–21] The model demonstrated excellent discrimination and calibration, with ROC curves, Hosmer–Lemeshow tests, and calibration plots indicating strong generalizability across both the training and validation cohorts (Figure 4). Furthermore, decision curve analysis (DCA)[22] confirmed the significant clinical net benefit in both cohorts, supporting its potential utility in personalized airway management (Figure 4e and f).

A critical distinction between our model and conventional airway assessment tools such as Look, Evaluate, Mallampati, Obstruction, Neck mobility (LEMON) and the Mallampati classification lies in their fundamental clinical objectives. While LEMON and Mallampati are well validated for predicting difficult laryngoscopy and intubation in elective settings,[23–26] they were not designed to assess the need for airway intervention in patients with active, spreading craniofacial infections. These established tools focus primarily on static anatomical features that may be obscured or rendered irrelevant by the rapid soft tissue changes, edema, and trismus characteristic of OMSI.[27,28] In contrast, our model addresses specifically the dynamic pathophysiology of OMSI by integrating real-time inflammatory markers (CRP level, sIL-2R level, and temperature), physiological parameters (dyspnea), and infection-specific anatomical factors (primary site involvement) that collectively capture the evolving risk of airway compromise in this distinct patient population.

OMSI are severe conditions characterized by rapid onset and progression and often spread from a single space to multiple regions, potentially leading to cellulitis, tissue necrosis, and abscess formation.[6] If untreated, infection can extend to orbital or intracranial spaces or into the mediastinum or lungs, causing airway obstruction or jugular vein thrombosis.[27–29] In severe cases, descending necrotizing mediastinitis (DNM)—a life-threatening complication with a reported incidence as high as 56.06%—can develop.[30] Despite advances in surgical techniques, imaging, and antibiotics, morbidity and mortality due to inadequate airway management persist.[31,32] Deep neck abscesses resulting from such infections can cause airway deformation, edema, and narrowing, culminating in dyspnea, which is present in approximately 11% of patients upon admission.[8,33] However, dyspnea alone is an insufficient predictor. Previous studies have reported that the percentage of OMSI patients ultimately requiring airway management ranges from 16.8% to 38.2%, whereas the percentage of patients who present with dyspnea upon hospital admission is only 5.6% to 12.8%.[34–36] This underscores the need for multivariable assessment.

The key novel component of our model is the inclusion of sIL-2R, a marker of T-lymphocyte activation.[37] Its predictive utility suggests that assessing the adaptive immune response offers prognostic insight beyond general inflammation markers such as CRP. This finding aligns with that of our previous work indicating the value of the sIL-

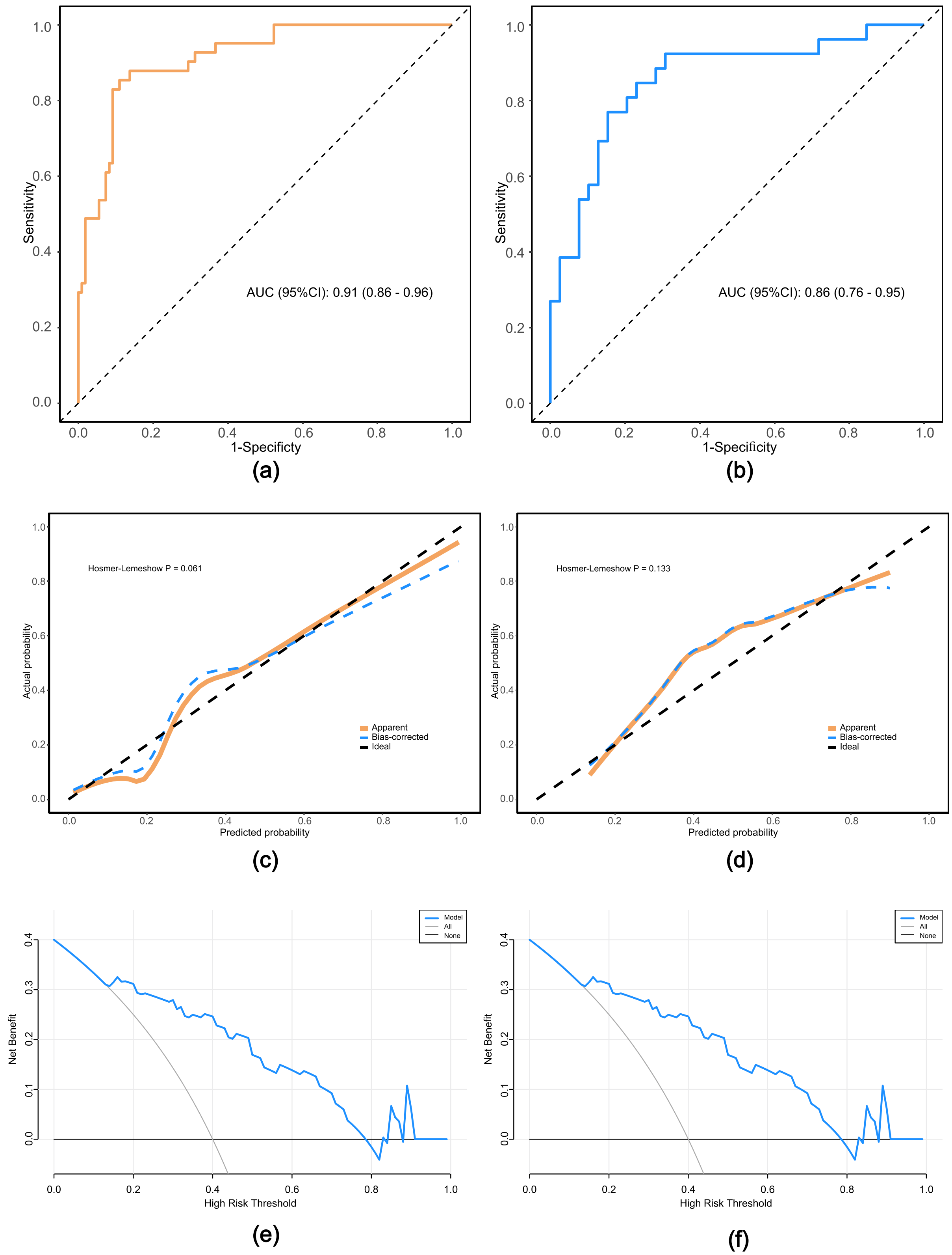

Figure 4 Performance of the prediction model. The receiver operating characteristic (ROC) curves demonstrate the model's discriminatory ability in the training cohort (**a**) and the validation cohort (**b**). Calibration curves show the agreement between predicted probabilities and actual outcomes in the training (**c**) and validation (**d**) cohorts. Decision curve analysis (DCA) curves illustrate the clinical benefits in the training cohort (**e**) and the validation cohort (**f**).

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2R level in distinguishing severe infections[38] and supports the integration of immune-specific biomarkers into risk stratification. CRP level, widely used to detect inflammation,[39] has also been implicated in predicting DNM,[16] further supporting its role in our model.

A critical question posed by this research is whether such a proposed scoring system offers a tangible advantage over the nuanced, experience-based assessment of a skilled clinician. We argue that it does not replace clinical judgment but rather augments it with objective, quantifiable, and reproducible data. While an experienced surgeon may intuitively recognize the perils of a retropharyngeal infection or a rising CRP, our model synthesizes these disparate clues into a single, standardized risk probability. This is particularly valuable in high-stress, time-sensitive environments for less experienced practitioners or in situations where senior decision makers are not immediately available.[40,41]

The question remains whether this scoring system offers tangible advantages over experienced clinical evaluation supplemented by imaging. We argue that its value lies not in replacing judgment but in augmenting it with reproducible, quantifiable data. By combining disparate clues—such as infection location (eg, retropharyngeal involvement, which confers a high risk for mediastinal spread and difficult airway),[42] inflammatory markers, and physiological parameters—into a standardized probability, the model may reduce variability in assessment, especially in high-acuity settings, during off-hours, or for less experienced clinicians. It also offers a common evidence-based framework for interdisciplinary communication.

This study has several limitations that should be acknowledged. First, its retrospective, single-center design and modest sample size (n = 215) may introduce selection bias and limit the generalizability of the findings. Although LASSO regression was used to mitigate overfitting and rigorous internal validation was performed, the absence of external validation remains an important constraint. Additionally, owing to the retrospective nature of the study, the clinicians involved in data collection were not blinded to patient outcomes, which may have introduced assessment bias. Although the model relies heavily on objective parameters—such as laboratory values, BMI, and anatomically defined infection sites—to minimize subjectivity, the potential for bias cannot be fully excluded. Furthermore, the exclusion of certain predictors due to missing data and the specific characteristics of the patient population from a single tertiary hospital may affect the broader applicability of the model. Future multicenter prospective studies with larger sample sizes are essential to validate and refine this risk score, increase its generalizability, and facilitate its integration into clinical practice. We also plan to incorporate quantitative imaging biomarkers and evaluate the model's impact on clinical decision-making and patient outcomes through implementation studies.

Conclusion

In this study, we developed and validated a risk scoring model that demonstrated a strong ability to predict airway management requirements in patients with OMSI. By facilitating the early identification of high-risk patients, this tool has the potential to trigger timely multidisciplinary consultation and intervention, which is critical for preventing catastrophic airway complications. While prospective validation is warranted, the implementation of this model could contribute to optimizing resource allocation and improving clinical decision-making, thereby potentially enhancing patient outcomes.

Ethics Statement

This study was conducted in accordance with the Declaration of Helsinki and was approved by the institutional review board of Shanghai Jiao Tong University School of Medicine (Approval No. SH9H-2024-T155-1). Due to the retrospective nature of the study, the Ethics Committee waived the requirement for individual patient informed consent. To protect patient privacy, all personal identifiers were removed from the data before analysis, ensuring patient data confidentiality.

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.

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Disclosure

The authors report no conflicts of interest in this work.

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