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RESEARCH

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Development and validation of a nomogram for predicting critical respiratory events during early anesthesia recovery in elderly patients

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Abstract

Background Elderly patients undergoing recovery from general anesthesia face a heightened risk of critical respiratory events (CREs). Despite this, there is a notable absence of effective predictive tools tailored to this specific demographic. This study aims to develop and validate a predictive model (nomogram) to address this gap. CREs pose significant risks to elderly patients during the recovery phase from general anesthesia, making it an important issue in perioperative care. With the increasing aging population and the complexity of surgical procedures, it is crucial to develop effective predictive tools to improve patient outcomes and ensure patient safety during post-anesthesia care unit (PACU) recovery.

Methods A total of 324 elderly patients who underwent elective general anesthesia in a grade A tertiary hospital from January 2023 to June 2023 were enrolled. Risk factors were identified using least absolute shrinkage and selection operator (LASSO) regression. A multivariate logistic regression model was constructed and represented as a nomogram. Internal validation of the model was performed using Bootstrapping. This study followed the TRIPOD checklist for reporting.

Results The indicators included in the nomogram were frailty, snoring, patient-controlled intravenous analgesia (PCIA), emergency delirium and cough intensity at extubation. The diagnostic performance of the nomogram model was satisfactory, with AUC values of 0.990 and 0.981 for the training set and internal validation set, respectively. The optimal cutoff value was determined to be 0.22, based on a Youden index of 0.911. The F1-score was 0.927, and the MCC was 0.896. The calibration curve, Brier score (0.046), and HL test demonstrated acceptable consistency between the predicted and actual results. DCA revealed high net benefits of the nomogram prediction across all threshold probabilities.

Conclusions This study developed and validated a nomogram to identify elderly patients in the PACU who are at higher risk of CREs. The identified predictive factors included frailty condition, snoring syndrome, PCIA, emergency delirium, and cough intensity at extubation. By identifying patients at higher risk of CREs early on, medical

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professionals can implement targeted strategies to mitigate the occurrence of complications and provide better postoperative care for elderly patients recovering from general anesthesia.

Keywords Postanesthesia care unit, Elderly patients, Critical respiratory events, Prediction model, Nomogram

Introduction

With the rise in global life expectancy and improvements in surgical safety, an increasing number of elderly surgical patients are opting for radical surgery to achieve better curative effects and enhance their quality of life [1]. During the early stage of emergence from general anesthesia, the patient's autonomous breathing gradually recovers. Due to residual neuromuscular block, respiratory depression caused by opioid drugs, incomplete metabolism of sedative drugs, and the combined effects of various other factors, some patients experience respiratory insufficiency, upper airway obstruction, diminished pharyngeal reflex, decreased muscle coordination, inadequate ventilation, increased risk of aspiration, and other critical respiratory events (CREs) after removal of the endotracheal tube [2, 3]. Elderly patients are at a heightened risk of experiencing CREs during the recovery phase following general anesthesia due to decreased respiratory reserves, impaired gas exchange, chest wall stiffness, weakened respiratory muscles, reduced lung elastic recoil, increased lung closing volume, diminished alveolar surface area, lower lung compliance, and reduced sensitivity of the respiratory center to hypoxia and hypercapnia. Additionally, multiple comorbidities and imbalances in perioperative stress responses further exacerbate this risk [4]. The incidence of respiratory-related complications in patients after general anesthesia in the post-anesthesia care unit (PACU) can reach 22.1%, the highest proportion being among elderly patients (≥65 years old) [5, 6]. Severe hypoxemia caused by CREs is an independent risk factor for prolonged postoperative hospital stay. It is closely associated with cerebral dysfunction adverse cardiovascular events and can even progress to respiratory and cardiac arrest [7].

Effective prevention of respiratory events during the recovery period requires assessing the risk factors for CREs and providing targeted interventions based on the risk level. Hence, there is an urgent need to construct a risk prediction model for adverse respiratory events that is suitable for clinical scenarios in the PACU. Existing models for predicting critical respiratory events (CREs) during the recovery period have several limitations. For example, the model developed by Wang et al. [8] is applicable only to patients extubated and then transferred to the PACU for recovery, without accounting for differences in distances between operating rooms and transport times. Additionally, the model's definition of hypoxemia ($SpO2<95\%$ for more than 15 s) can often be corrected without pharmacological intervention in general patients, limiting its clinical relevance. Liu et al. [4] constructed a model based on electronic medical record data through retrospective study and validation, targeting all patients who developed hypoxemia in the PACU. However, this model may suffer from missing important variables from the electronic medical records, and missing data were not addressed during validation. Other studies focus on specific pulmonary complications such as postoperative pneumonia [9], respiratory failure [10], unplanned reintubation [11, 12], and adult respiratory distress syndrome [13, 14], making these models suitable only for specific diseases and clinical settings. Moreover, there are no specific models developed for CREs in patients during the recovery phase from general anesthesia. Some models also lack external data validation, which limits their reproducibility, generalizability, and applicability.

Thus, this study aimed to investigate the risk factors for CREs in elderly patients during the recovery period after general anesthesia and to establish a risk prediction model. On the basis of multiple regression analysis, the complex regression equation was transformed into a nomogram, a visual tool to help healthcare providers quickly screen high-risk patients for CREs. This nomogram will enable the early implementation of personalized interventions, ultimately reducing the incidence of CREs among elderly patients.

Aims

This study aims to identify risk factors associated with CREs in elderly patients during post-anesthesia recovery, develop a nomogram model, and assess its predictive performance.

Methods

This prospective cohort study was conducted in accordance with all relevant guidelines and regulations, including the Declaration of Helsinki. Additionally, the research adhered to the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) checklist, ensuring comprehensive and transparent reporting of the methods and findings.

Study participants

A convenience sampling method was employed to select elderly patients who underwent elective surgery under general anesthesia in a comprehensive tertiary grade A hospital from January 2023 to June 2023. The inclusion criteria were as follows: (1) age ≥65 years; (2) intravenous inhalation combined anesthesia; (3) preoperative $SpO_2 \geq 94\%$ (oxygen inhalation); and (4) complete database data. Exclusion criteria were as follows: (1) surgery related to obstructive sleep apnea; (2) cardiac surgery; (3) tracheostomy; (4) hypoxia due to hemodynamic instability; (5) inability to communicate normally due to barriers such as dementia, severe hearing loss and language communication issues; (6) transfer to the intensive care unit (ICU) after surgery; and (7) transfer to the PACU after extubation. The sample size was estimated based on the overall rate [15]: $n = \frac{Z^2{}_{\alpha/2}P(1-P)}{\delta^2}$, where P is the overall rate, and δ is the allowable error. δ = 0.05, α = 0.05, and the incidence of CREs in elderly patients was 25% based on our preliminary studies. Accounting for a potential loss to follow-up of 15%, the final sample size was calculated to be 339 cases. Therefore, in this study, 339 elderly patients who had undergone general anesthesia were initially included.

Definition and identification of CREs

Based on the revised Murphy standard [16] and a literature review [17, 18], combined with clinical practice standards, the criteria for CREs in this study were as follows: (1) upper airway obstruction, patients need to receive the following interventions: oropharyngeal airway, nasopharyngeal airway, and airway opening. (2) mild–moderate hypoxemia (SpO_2: 90–93%) under a nasal cannula or mask oxygen inhalation with no improvement after active interventions, such as increasing the oxygen flow, at least two verbal reminders to take deep breaths, tactile stimulation, and drug intervention (e.g., doxapram); (3) severe hypoxemia ($SpO_2 < 90\%$) under a nasal cannula or mask oxygen inhalation, with no improvement after active interventions, such as increasing the oxygen flow, ≥2 verbal reminder to take deep breaths, tactile stimulation, and drug intervention (e.g., doxapram); (4) hypoxemia accompanied by poor consciousness, inability to breathe deeply, and ineffective drug intervention, requiring Ambu-bags/manual resuscitation; and (5) ventilator-assisted ventilation, tracheal reintubation, or noninvasive positive pressure ventilation. Meeting any one criterion was defined as a CRE during recovery. Assessments for CREs were conducted immediately upon arrival at the PACU and monitored continuously for the first 30 min post-surgery. Subsequent evaluations were performed at 5-minute intervals until the patient was discharged from the PACU. All assessments were conducted by trained medical staff using standardized protocols and equipment to ensure consistency.

Instruments for data collection

Through a literature review and expert consultation, combined with clinical practice experience, a form for collecting information on risk factors for CREs in elderly patients was created. The form included the following content: (1) demographic data: age, sex, BMI, ASA grade, smoking history, frailty status (the FRAIL scale), etc.; (2) medical history: snoring, hypertension, diabetes, lung disease and hypohemia; (3) surgery-related factors: surgical site (e.g., oral and maxillofacial facial, neck, abdomen), surgical position (e.g., supine, lateral, lithotomy), and intraoperative irrigation; (4) anesthesia-related factors: artificial airway type, opioid dosage, type of muscle relaxant, anesthesia duration, drug antagonism before extubation; and (5) postoperative-related factors: patient-controlled intravenous analgesia (PCIA), emergence delirium (Nursing Delirium Screening Scale), cough intensity at extubation (Semiquantitative Cough Strength Score, SCSS, graded 0–5), and duration of tracheal intubation.

Data collection

All patients were given standardized anesthesia and analgesia. Anesthesia was induced with sufentanil citrate, propofol, cisatracurium/rocuronium bromide, sevoflurane, and remifentanil hydrochloride. Analgesia was administered via nerve block and/or analgesic pump guided by B-ultrasound. Intraoperative blood pressure was maintained at approximately ±20% of the baseline level, and the depth of anesthesia was monitored with the bispectral index, which we kept at 40–60. Muscle relaxants were discontinued 20 min before the end of surgery. Inhalation of sevoflurane was stopped 15 min before skin suture. The propofol pump was ended after surgery. Tracheal extubation was performed strictly following extubation indications, that is, the patient could cooperate with commanded actions, such as opening the eyes, the patient's vital signs were stable, the patient could lift his or her head off the bed surface for 5–10 s, and the patient had a strong fist as an evaluation of muscle strength and a tidal volume under spontaneous breathing of 6–8 ml/kg. The timing of extubation was determined jointly with the anesthesiologist. After extubation, a nasal cannula or mask was used to deliver oxygen to the patient.

All PACU nurses completed standardized training on the criteria for identifying CREs, screening for delirium during recovery, standardized extubation procedures, and the assessment of cough intensity. One day before the operation or in the preoperative preparation room, a researcher collected each patient's general information and conducted frailty screening using the FRAIL scale, as well as an evaluation using the Charlson comorbidity index (CCI). After the operation, information related to surgery and anesthesia was obtained by reviewing electronic records. Cough intensity and delirium were assessed immediately after extubation, while respiration and oxygenation were assessed every 5 min. Any abnormalities were promptly assessed and addressed.

Statistical analyses

Strict quality control measures ensured that there were no missing data. Complete case analysis was employed. Data analyses were performed with RStudio software. Measurement data that did not conform to a normal distribution are expressed as median (P25, P75), and the nonparametric Mann-Whitney U test was used for intergroup comparisons. Count data are presented as frequency (percentages), and the chi-squared test was applied for intergroup comparisons. For the univariate analysis (UA), age, BMI, ASA grade, frailty condition, and intraoperative opioid dosage were included as ordinal variables. CCI, fluid balance, anesthesia duration, cough intensity at extubation, and duration of tracheal intubation were included as continuous variables. All other factors were included as nominal variables. Least absolute shrinkage and selection operator (LASSO) regression was employed to screen for variables that were statistically significant in the UA. This approach helps address the issue of multiple cross-correlated covariates and reduces the risk of overfitting the data. To further ensure the robustness of our model, we used 10-fold cross-validation to select the optimal lambda parameter, considering the minimum standard error.

We employed Bootstrap resampling for internal validation. This technique helps in estimating the accuracy of the model and reduces the risk of overfitting by repeatedly sampling from the dataset with replacement and evaluating the model on these samples. Model discrimination was evaluated in the form of the area under the receiver operating characteristic (ROC) curve (AUC), F1 score, and Matthews correlation coefficient (MCC). The optimal AUC cutoff was determined by maximizing the Youden index. Calibration curves, the Hosmer−Lemeshow goodness-of-fit test, and the Brier score were used to assess the agreement between the observed and predicted results. The net clinical benefit was evaluated using decision curve analysis (DCA).

Results

Study population

Fifteen were excluded for not meeting the criteria, including preexisting hypoxemia with $SpO2 < 94\%$ (four), postoperative transfer to the ICU (four), post-extubation admission to the PACU (five), and severe hearing impairment preventing communication (two). Ultimately, 324 patients were included in the study, 95 (29.32%) of whom experienced CREs during emergence from anesthesia. The subjects included in the study were between 65 and 91 years of age, with an average age of 71.09 ± 5.444. The average age in the CRE group was 72.62 ± 6.637 years, and the average age in the non-CRE group was 70.45 ± 4.736 years. The time of appearance of CREs was between 3 and 25 min, with an average time of 5.83 ± 2.872 min. Among the 95 patients with CREs, 2 (2.11%) had upper airway obstruction, 32 (33.68%) had mild to moderate hypoxemia, 48 (50.53%) had severe hypoxemia, 9 (9.47%) required Ambu-bags/manual resuscitation, and 4 (4.21%) received secondary tracheal intubation.

To avoid missing important variables, the test level in the UA was set to 0.10. The results of UA (Table 1) showed that there were significant differences between non-CRE patients and CRE patients in age, BMI, ASA grade, CCI, smoking, frailty, snoring, hypertension, lung disease or other complications, anemia, surgical position, fluid balance, artificial airway type, intraoperative opioid dosage, anesthesia duration, drug antagonism before extubation, PCIA, emergence delirium, cough intensity at extubation, and duration of tracheal intubation ($P < 0.1$).

Predictor variable filtering by LASSO regression

The 20 risk factors that exhibited significant differences in the initial analysis were further analyzed using LASSO regression to reduce dimensionality and identify the most important predictors. The optimal parameter (lambda) for the LASSO model was chosen through 10-fold cross-validation, considering the minimum standard error. The number of variables with non-zero regression coefficients was determined and depicted in Fig. 1. The results of the LASSO regression revealed that frailty, snoring, anemia, intraoperative opioid dosage, PCIA, emergence delirium, and cough intensity at extubation were identified as risk factors for CREs in elderly patients during recovery from general anesthesia.

Multivariate logistic regression model construction

Logistic regression was employed to verify these risk factors. The occurrence of CREs was considered the dependent variable, while the seven risk factors screened by LASSO regression were input as the independent variables for multiple logistic regression analysis. The independent variables were assigned as follows: frailty: 1= “no frailty”, 2= “prefrailty”, and 3= “frailty”; intraoperative opioid dosage and cough intensity at extubation (continuous variables): original values; and other variables: 0 = no, and 1 = yes. The results indicated that five variables, namely frailty, snoring, PCIA, emergence delirium and cough intensity at extubation, were independent risk factors for CREs in elderly patients during recovery from general anesthesia ($P < 0.05$, Table 2). The model was constructed as follows: Logit (P) = 0.153 + 4.107×(frailty) + 3.006×(snoring) + 1.999×(PCIA) + 1.956×(emergence delirium)-2.679×(cough intensity at extubation).

To facilitate prediction, a nomogram was developed based on these predictors, representing a prediction model for CREs in elderly patients during recovery from general anesthesia (Fig. 2). By utilizing the variable

Table 1 Comparison of risk factors associated with CREs between the groups

Variables	Total (*n*=324)	CREs (*n*=95)	Non-CREs (*n*=229)	Statistical value	*P*-value
Sociodemographic					
Age(years)				**11.421**	**0.010***
65～69	155 (47.84%)	39 (41.05%)	116 (50.66%)		
70～74	96 (29.63%)	25 (26.32%)	71 (31.00%)		
75～79	46 (14.20%)	16 (16.84%)	30 (13.10%)		
≥80	27 (8.33%)	15 (15.79%)	12 (5.24%)		
Gender				0.762	0.383
Male	186 (57.41)	51 (53.68)	135 (58.95)		
Female	138 (42.59)	44 (46.32)	94 (41.05)		
BMI (kg/m^2)				**10.420**	**0.015***
<18.5 (underweight)	14 (4.32%)	9 (9.47%)	5(2.18%)		
18.5～23.9 (normal)	138 (42.59%)	33 (34.74%)	105 (45.85%)		
≥24 (overweight)	128 (39.51%)	39 (41.05%)	89 (38.86%)		
≥28 (obesity)	44 (13.58%)	14 (14.74%)	30 (13.10%)		
ASA grade				**43.229**	**< 0.001*****
I	15 (4.63%)	0 (0.00%)	15 (6.55%)		
II	266 (82.10%)	65 (68.42)	201 (87.77%)		
III	43 (13.27%)	30 (31.58%)	13 (5.68%)		
CCI△	4.0 (4.0,5.0)	5.0 (5.0,7.0)	4.0 (4.0,5.0)	**-8.264**	**< 0.001*****
Smoking				**18.010**	**< 0.001*****
Yes	93 (28.70)	43 (45.26)	50 (21.83)		
No	231 (71.30)	52 (54.74)	179 (78.17)		
Frailty condition				**130.610**	**< 0.001*****
No frailty	105 (32.41%)	2 (2.11%)	103 (44.98%)		
Pre- frailty	106 (32.72%)	16 (16.84%)	90 (39.30%)		
Frailty	113 (34.88%)	77 (81.05%)	36 (15.72%)		
Medical history					
Snoring syndrome				**24.619**	**< 0.001*****
Yes	214 (66.05%)	82 (86.32%)	132 (57.64%)		
No	110 (33.95%)	13 (13.68%)	97 (42.36%)		
Hypertension				**6.750**	**0.013***
Yes	148 (45.68%)	54 (56.84%)	94 (41.05%)		
No	176 (54.32%)	41 (43.16%)	135 (58.95%)		
Diabetes				0.489	0.484
Yes	171 (52.78%)	53 (55.79%)	118 (51.53%)		
No	153 (47.22%)	42 (44.21%)	111 (48.47%)		
Lung disease or other complications				**13.722**	**< 0.001*****
Yes	93 (28.70%)	41 (43.16%)	52 (22.71%)		
No	231 (71.30%)	54 (56.84%)	177 (77.29%)		
Anemia				**6.551**	**0.010***
Yes	55 (16.98%)	24 (25.26%)	31 (13.54%)		
No	269 (83.02%)	71 (74.74%)	198 (86.46%)		
Surgical related factors					
Surgical site				7.760	0.170
Oral and maxillofacial	10 (3.09%)	0 (0.00%)	10 (4.37%)		
Check	17 (5.25%)	4 (4.21%)	13 (5.68%)		
Neck	41 (12.65%)	17 (17.89)	24 (10.48%)		
Abdomen	192 (59.26%)	54 (56.84)	138 (60.26%)		
Epidermis of extremities	28 (8.64%)	8 (8.42%)	20 (8.73%)		
Thoracolumbar	36 (11.11%)	12 (12.63%)	24 (10.48%)		
Surgical position				12.092	**0.007****
Supine	164 (50.62%)	44 (46.32%)	120 (52.40%)		

Table 1 (continued)

Variables	Total (*n*=324)	CREs (*n*=95)	Non-CREs (*n*=229)	Statistical value	*P*-value
Lateral	48 (14.81%)	24 (25.26%)	24 (10.48%)		
Lithotomy	75 (23.15%)	17 (17.89%)	58 (25.33%)		
Prone	37 (11.42%)	10 (10.53%)	27 (11.79%)		
Intraoperative irrigation				0.660	0.416
Yes	222 (68.52%)	62 (27.93%)	160 (72.07%)		
No	102 (31.48%)	33 (32.35%)	69 (67.65%)		
Fluid balance (ml) △	897.5 (498.0,1012.5)	900.0 (697.5,1292.0)	870.0 (498.0,998.0)	**-1.945**	**0.052**
Anesthesia related factors					
Artificial airway type				**9.002**	**0.003****
Laryngeal mask airway	273 (84.26%)	89 (93.68%)	184 (80.35%)		
Tracheal intubation	51 (15.74%)	6 (6.32%)	45 (19.65%)		
Intraoperative Opioid dosage(ug)△	34.5 (30.0,40.0)	40.0 (30.0,45.0)	30.0(30.0,40.0)	**-5.123**	**< 0.001*****
Types of muscle relaxants				0.077	0.781
Rocuronium bromide	130 (40.12%)	37 (38.95%)	93 (40.61%)		
Cis-atracurium	194 (59.88%)	58 (61.05%)	136 (59.39%)		
Anesthesia duration (min) △	110.0 (65.0,175.0)	150.0 (89.5,210.0)	95.0 (60.0,155.0)	**-4.389**	**< 0.001*****
Drug antagonism before extubation				**7.939**	**0.005****
Yes	53 (16.36%)	7 (7.37%)	46 (20.09%)		
No	271 (83.64%)	88 (92.63%)	183 (79.91%)		
Postoperative Related factors					
PCIA					
Yes	122 (37.65%)	64 (67.37%)	58 (25.33%)	**50.552**	**< 0.001*****
No	202 (62.35%)	31 (32.63%)	171 (74.67%)		
Emergence delirium					
Negative	103 (31.79%)	68 (71.58%)	35 (15.28%)	**98.133**	**< 0.001*****
Positive	221 (68.21%)	27 (28.42%)	194 (84.72%)		
Cough intensity at extubation△	3.0 (2.0 to 4.0)	2.0 (2.0 to 2.0)	4.0 (3.0 to 4.0)	**12.807**	**< 0.001*****
Duration of tracheal intubation (min)△	140.0 (95.0,205.0)	175.0(109.5,252.5)	135.0(90.0,180.0)	**-4.077**	**< 0.001*****

Note: △ The variable was represented using the median and interquartile range. † Statistic based on Chi-square test (χ^2 value) ;‡ Statistic based on Mann-Whitney U test (*Z* value). **P* < 0.05, ***P* < 0.01, ****P* < 0.001. Bold font indicates *P*<0.1. Anemia diagnosis: Hemoglobin levels below 12.0 g/dL for adult males and below 11.0 g/dL for adult females. BMI, Body Mass Index; ASA, American Society of Anesthesiologists; CCI, Charlson Comorbidity Index; PCIA, Patient-Controlled Intravenous Analgesia

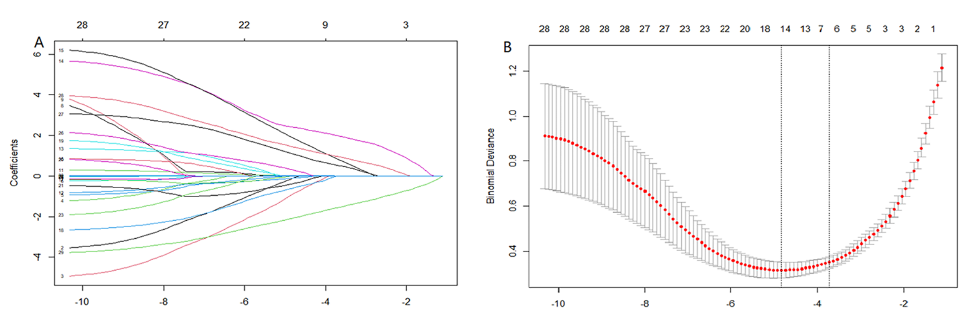

Fig. 1 The LASSO regression model was used to select characteristic impact factors: (**A**) LASSO coefficients of 28 features; (**B**) selection of the tuning parameter (λ). The left and right dotted vertical lines, respectively, represented the optimal lambda values when using the minimum error criterion and one standard error (1se) of the minimum criterion (lambda.1se = 0.02420579)

classifications in the nomogram, one can obtain scores corresponding to each index. These scores are summed to calculate the total score, and the predicted probability corresponding to the total score represents the likelihood of CREs occurring in elderly patients during PACU resuscitation. As an example, taking an elderly patient after general anesthesia who exhibits a cough intensity of 1 point at extubation, positive delirium during recovery, PCIA, no history of snoring, and pre-frailty, the predicted probability that such a patient will have a CREs is 94.5%.

Table 2 Multivariate logistic regression analysis of the risk of CREs in elderly patients during recovery from general anesthesia

Variables	Category	Coefficients	St. Error	Wald χ^2	OR (95% CI)	*P*-value
Constant	-	0.153	1.682	0.091	-	-
Frailty condition (Ref: No frailty)	Pre-frailty	1.417	1.155	1.226	4.125(0.527–55.370)	0.220
	Frailty	4.107	1.139	3.607	60.771(8.803-880.524)	**<0.001**
Snoring syndrome (Ref: No)	Yes	3.006	0.832	3.612	20.213(4.448–120.700)	**<0.001**
PCIA (Ref: No)	Yes	1.999	0.684	2.922	7.380(2.052–31.317)	**0.003**
Emergence delirium (Ref: negative)	Positive	1.956	0.625	3.132	7.069(2.186–26.319)	**0.001**
Cough intensity at extubation	-	-2.679	0.468	-5.731	0.069(0.024–0.153)	**<0.001**

Note: Bold font indicates *P*<0.05

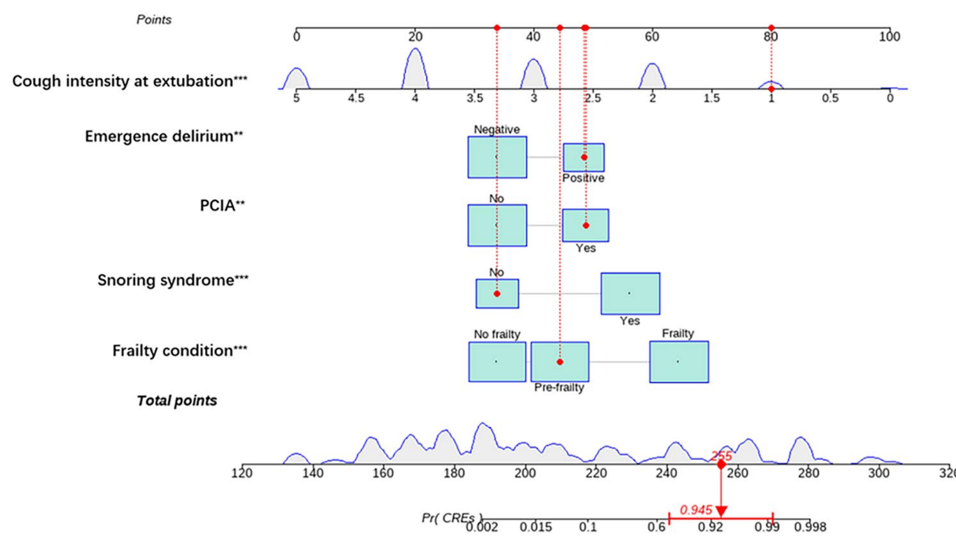

Fig. 2 A nomogram prediction model for CREs in elderly patients during recovery from general anesthesia

Nomogram model validation

The nomogram model's concordance index, also known as the C-index (equivalent to the area under the ROC curve AUC), was 0.990 (95% CI: 0.982–0.997), accompanied by a sensitivity of 0.943 (95% *CI*: 0.933-1.000) and a specificity of 0.968 (95% *CI*: 0.913–0.973) (Fig. 3). The optimal cutoff value of the nomogram score was determined to be 0.22, when the Youden index was 0.911. Internal verification through Bootstrapping with 1,000 resamples confirmed the robustness of the model, with a C-index of 0.981 (95% *CI*: 0.953–0.996), sensitivity of 0.961 (95% *CI*: 0.912-1.000), and specificity of 0.910 (95% *CI*: 0.784-1.000), demonstrating excellent model calibration. The detailed results are shown in Table 3. Furthermore, the F1-score was calculated to be 0.927 (95% *CI*: 0.882–0.969), and the MCC was 0.896 (95% *CI*: 0.882–0.969), both indicating the model's strong discriminating ability. The Hosmer−Lemeshow goodness-of-fit test yielded a result of χ^2=1.160, P=0.997, suggesting that the nomogram model was well-suited for predicting CREs in elderly patients during their PACU recovery after general anesthesia.

The Bootstrap resampling calibration curve (Fig. 4) illustrated that the probabilities of CREs predicted by the nomogram aligned well with the observed probabilities, and the model calibration curve closely resembled that of an ideal model. The Brier value of 0.046 (95% *CI*: 0.024–0.055) indicated that the nomogram model effectively predicted the occurrence of CREs in elderly patients during recovery from general anesthesia, exhibiting strong internal sampling calibration and reliable correlations.

Clinical utility of the nomogram

The DCA of the nomogram is presented in Fig. 5. The horizontal axis represents the threshold probability, while the vertical axis represents the net benefit. The interventions mentioned here referred to any behavioral or external factors taken into account when the model identified high-risk patients. The black line in the graph, parallel to the X-axis, represents the scenario where no clinical intervention is performed for any patients. The red line represents the model's decision curve. A high-quality predictive model should ensure that within a certain threshold probability range, or at least at a specific threshold probability level, the net benefit is higher than the net benefits associated with the two reference lines of "full intervention" and "no intervention." As observed in Fig. 5, the net benefit of the model's decision curve

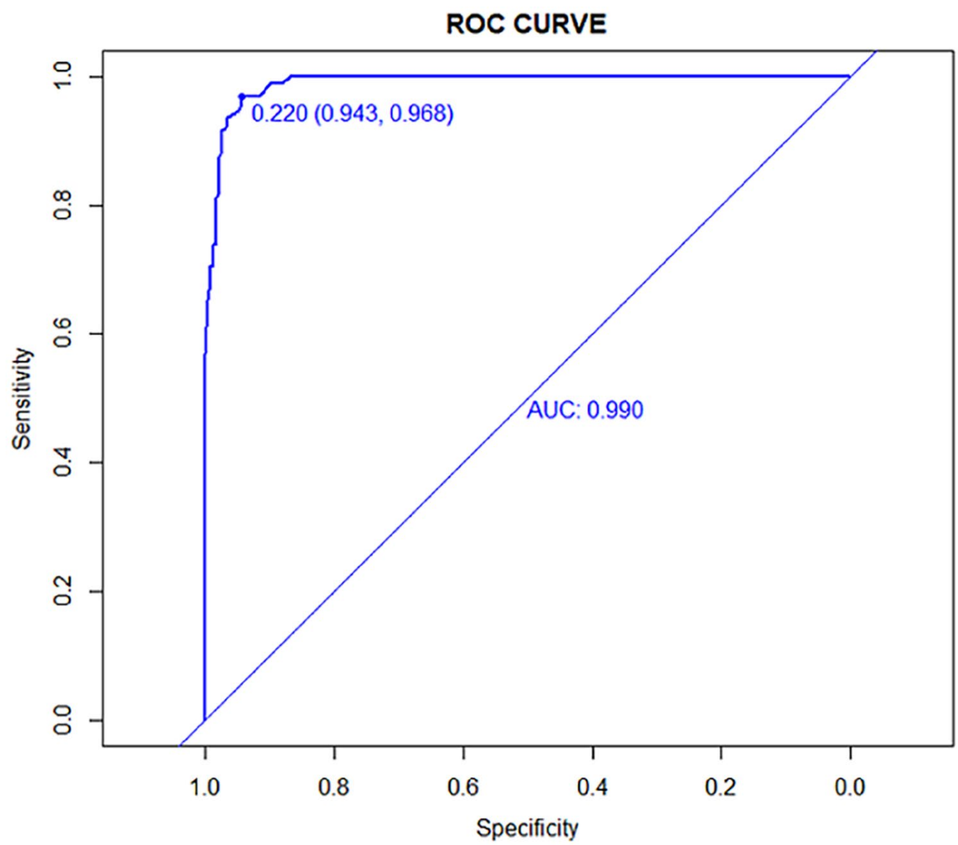

Fig. 3 Receiver operating characteristic (ROC) curve of the nomogram

Table 3 Summary of model performance metrics

Metric	Modeling phase	Validation phase (Bootstrap)
C-index (AUC)	0.990 (95% *CI*: 0.982–0.997)	0.981 (95% *CI*: 0.953–0.996)
Sensitivity	0.943 (95% *CI*: 0.933-1.000)	0.961 (95% *CI*: 0.912-1.000)
Specificity	0.968 (95% *CI*: 0.913–0.973)	0.910 (95% *CI*: 0.784-1.000)

consistently surpassed the net benefits of the two null lines for all threshold probabilities. This suggests that the nomogram model exhibits good clinical applicability and can be a valuable tool in identifying high-risk patients and aiding in clinical decision-making.

Discussion

Hypoxemia caused by CREs is the most common postoperative complication observed in the PACU. In this study, the incidence of CREs in elderly patients was found to be 29.32%, which was higher than the rates reported by Liu et al. (17.5%) [4] and Zhu et al. (21.19%) [19]. This discrepancy can be attributed to differences in study populations and outcome measurement criteria. Specifically, this study focused on elderly patients, a high-risk group for CREs, and used SpO2% as an indicator, which is more sensitive and accessible than the oxygenation index used in previous studies.

In our research, a nomogram was developed to predict CREs in elderly patients during recovery from general anesthesia. The model showed good discrimination and calibration. Unlike traditional logistic regression, this study used LASSO regression to reduce dimensionality and multicollinearity, effectively selecting variables by balancing variance and bias. Nomograms combine multiple predictors, offering higher predictive sensitivity and specificity compared to single predictors. This makes them more scientific and practical for predicting CREs in elderly patients during the PACU recovery period. Specifically, several variables were identified as strong predictors of CREs in elderly patients in the PACU, including frailty, snoring, PCIA, emergence delirium, and cough intensity at extubation.

Frailty is a clinical syndrome characterized by a decline in the multiorgan system reserve capacity, mainly related to decreases in strength, endurance, physical function, and maintenance of homeostasis [20]. It has been significantly correlated with both short-term and long-term surgical outcomes [21, 22]. A recent study also manifested that frail elderly patients undergoing thoracoscopic lobectomy had a 2- to 3-fold-higher risk of

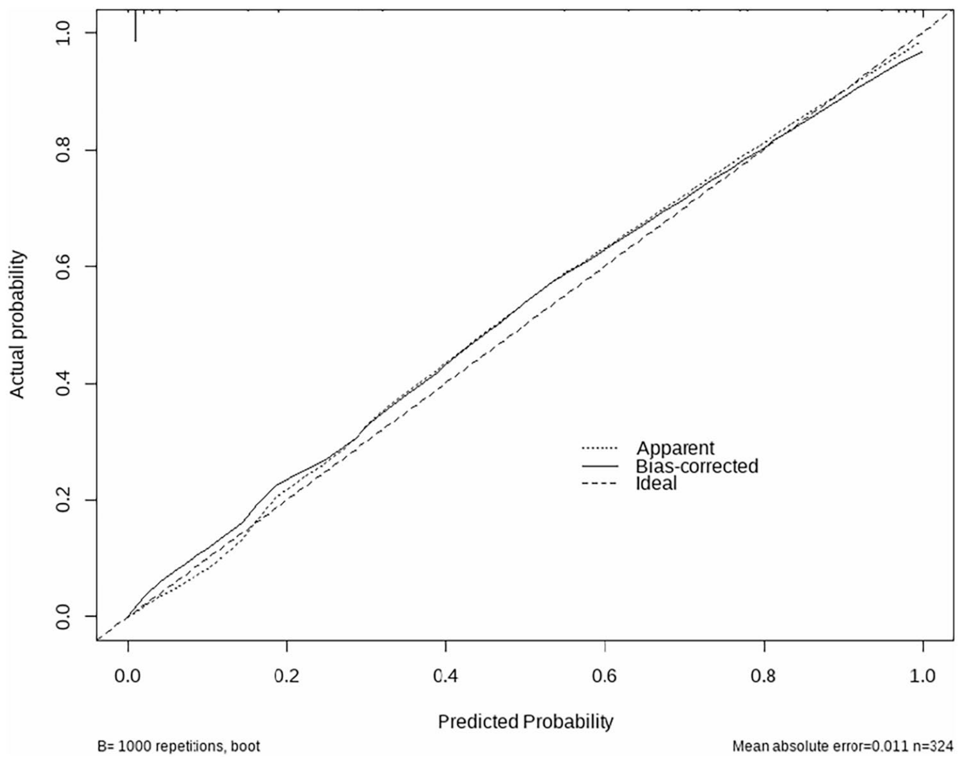

Fig. 4 Calibration curves of the nomogram. *Note*: The X-axis represented the predicted possible risk of severe respiratory events(CREs)after extubation. The Y-axis represented the actual diagnosed CREs. The dashed line represents the original performance, and the solid dashed line represents the performance during internal validation by Bootstrapping (B = 1,000 repetitions)

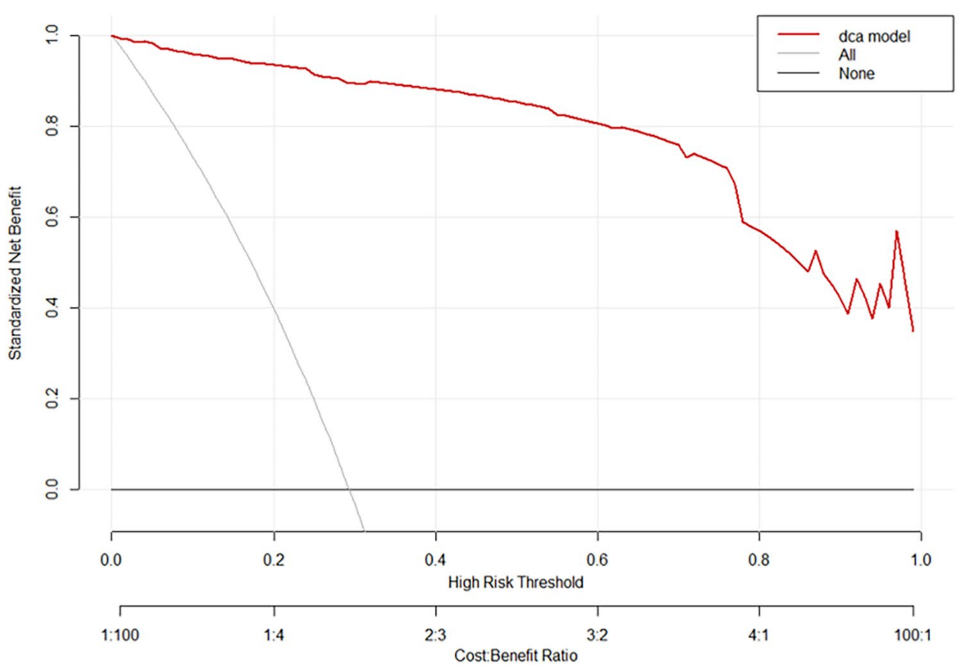

Fig. 5 Decision curve analysis for the nomogram model

postoperative pulmonary complications than non-frailty elderly patients [23]. This finding was further supported in the present study, which showed that preoperative frailty not only correlated with long-term lung disease but also strongly predicted the risk of CREs in the early postoperative period. Another finding of this study is that patients who snored had a higher likelihood of developing CREs after surgery. Snoring often described as a rough and vibrating sound caused by partial obstruction of inspiration in the oropharynx during sleep [24], can be considered the initial stage of a spectrum of sleep-disordered breathing, which encompasses a range from partial airway collapse to mildly increased upper airway resistance to complete airway collapse and severe obstructive sleep apnea (OSA) lasting for 60 s or longer [25]. The intermittent vibrations due to turbulent air cause local inflammation and edema around the uvula, soft palate, and upper airway, thereby increasing airflow resistance and potentially causing or worsening airway obstruction during recovery from anesthesia [26].

Interestingly, the final regression model did not include intraoperative opioid dosage as a significant factor, even though PCIA drugs containing opioids were identified as a risk factor for CREs in elderly patients during recovery. This may be due to standardized intraoperative opioid doses and the lack of tracking total PCIA opioid use. In clinical practice, preemptive analgesia is often applied, where analgesics are administered through PCIA before the patient wakes up. Elderly patients, with reduced cerebral blood flow and metabolic function, are at high risk for emergence delirium [27]. Post-extubation excitement and restlessness, sometimes attributed to pain, may lead to the addition of opioids to the PCIA pump, which can impair respiratory control and upper airway function, causing central apnea, airway obstruction, and hypoxemia. This risk is particularly pronounced in patients with OSA, who are more susceptible to opioid-induced respiratory depression. Cognitive dysfunction in emergence delirium can hinder cooperation with medical staff, leading to decreased airway protection and subsequent hypoxemia. A recent study showed that intraoperative hypoxemia and hypocapnia increase the risk of postoperative delirium [28]. In addition to PCIA-related factors, cough intensity is a crucial indicator of a patient's ability to maintain airway patency after tracheal extubation. Successful gas exchange relies on the patient's capacity to keep an unobstructed airway and breathe independently. Inadequate cough strength, combined with excessive secretions, can lead to bronchial blockage, atelectasis, and aspiration pneumonia, contributing to CREs [25]. Khamiees et al. [29] used the SCSS (range, 0–5) to predict extubation success, finding that patients with SCSS ≤ 2 had a significantly higher risk of extubation failure. Wang [8] used SCSS to predict hypoxemia after extubation, consistent with this study's findings that SCSS is a protective factor against CREs.

The nomogram developed in this study provides several improvements over existing practices by integrating multiple predictors into a comprehensive risk assessment tool. This model enables clinicians to identify high-risk patients preoperatively and implement tailored perioperative management strategies. Upon identifying high-risk patients through the nomogram, healthcare providers can take several steps to improve patient outcomes. In the preoperative phase, comprehensive patient data should be collected. Perioperatively, multifactor interventions targeting exercise, cognition, and nutrition can help delay or reverse frailty. Complete sleep apnea monitoring is advisable for patients who snore, with appropriate treatment provided for those diagnosed with severe OSA before elective surgeries [26]. Preemptive analgesia should be used judiciously, ensuring standardized intraoperative opioid administration while closely monitoring PCIA opioid use. Postoperatively, enhancing airway protection awareness and monitoring for high-risk patients is crucial. Extubation may need to be delayed if necessary, and muscle relaxant monitoring devices should be used to accurately assess muscle strength and avoid postoperative CREs [30]. For patients with emergence delirium, adherence to standard PCIA protocols, prompt pain assessment, and appropriate adjustments in analgesic dosages are essential to minimize respiratory complications [28]. Additionally, assessing cough intensity through the SCSS post-extubation provides valuable insights into airway patency, helping to predict and prevent CREs. Educating patients on effective coughing techniques and ensuring timely clearance of secretions can further reduce CREs in high-risk patients. By integrating these steps into clinical practice, the nomogram model not only identifies high-risk patients but also guides specific interventions to enhance patient safety and outcomes during the postanesthesia recovery period.

It is important to pay attention to other potential risk factors that have shown promise in early warning systems, such as age, BMI, hyperlipidemia, intraoperative application of lavage fluid, prone position, hypertension, diabetes, postoperative hypothermia, and ASA grade [4, 8, 19]. Although these factors were not included in the current predictive model, they have been identified as potential indicators of complications during anesthesia recovery in previous studies. To establish a more comprehensive understanding of these risk factors and their significance in predicting complications, further verification is necessary through large-sample, multicenter studies. Such studies can yield more robust and reliable evidence regarding the role of these indicators in early warning systems. This will contribute to improving patient care and ensuring the safety of anesthesia procedures.

Limitations
This study has several limitations. The study population was derived from a single tertiary hospital, which may introduce selection bias and limit the generalizability of our findings to the broader population. The relatively small sample size may not capture the full variability in patient characteristics and outcomes. The variables used in our model were based on routine clinical measurements and records, which may be subject to inaccuracies and inconsistencies. Additionally, important variables such as intraoperative ventilator parameters and total opioid use in PCIA were not included, potentially introducing measurement bias. Although we employed multivariable logistic regression to adjust for known confounders, residual confounding factors could bias the observed associations between risk factors and CREs. Furthermore, the model's generalizability is a concern as it was developed using data from elderly patients undergoing elective general anesthesia in a tertiary care setting. This specific context may limit its applicability to other populations, such as different age groups, emergency surgeries, or various healthcare settings. The data were collected over a six-month period, and changes in clinical practices, patient management strategies, or healthcare policies over time could affect the model's performance. Continuous monitoring and periodic recalibration are necessary to maintain accuracy. Although internal validation through Bootstrapping confirmed the model's robustness, external validation in different clinical settings and populations is required to fully establish its generalizability. Future research should focus on validating the model in multiple centers with diverse patient populations.

Conclusions
In this study, several independent risk factors for complications during recovery from general anesthesia in elderly patients were identified frailty, snoring, PCIA, emergence delirium, and cough intensity at extubation. Based on these risk factors, a risk prediction nomogram for CREs in elderly patients in the PACU was developed. The nomogram demonstrated good discrimination, calibration, and clinical validity, making it a valuable tool for early clinical prediction of CREs in surgical elderly patients during postoperative recovery from general anesthesia. Thise nomogram can give medical personnel a scientific approach to CREs prevention and control, as well as precise interventions, based on individual risk factors. By identifying patients at higher risk of CREs early on, medical professionals can implement targeted strategies to mitigate the occurrence of complications and provide better postoperative care for elderly patients recovering from general anesthesia. This approach will improve patient outcomes and enhance the overall quality of care in surgical settings for the elderly population.

Abbreviations
CREs	Critical respiratory events
PACU	Post-anesthesia care unit
ICU	Intensive Care Unit
BMI	Body Mass Index
CCI	Charlson Comorbidity Index
PCIA	Patient-Controlled Intravenous Analgesia
ASA	American Society of Anesthesiologists
SCSS	Semiquantitative Cough Strength Score.
LASSO	Least absolute shrinkage and selection operator
ROC	Receiver Operating Characteristic
MCC	Matthews correlation coefficient
DCA	Decision Curve Analysis
SE	Standard Error
OSA	Obstructive Sleep Apnea

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Author contributions
Jingying Huang: Conceptualization, Methodology, Writing-Original draft preparation; Haiou Qi: Supervision, Writing-Reviewing and Editing; Xin Xu: Project administration.; Jin Yang and Yiting Zhu: Data collection; Miaomiao Xu：Data collection; Yuting Wang: Data curation.

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Data availability
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The study was carried out in strict adherence to the principles outlined in the Declaration of Helsinki. All procedures involving human participants were approved by the by the Institutional Review Board of Sir Run Run Shaw Hospital Affiliated to Zhejiang University School of Medicine (No. 2023539-01, Date: January 25, 2023)., and written informed consent was obtained from all participants prior to their inclusion in the study. Confidentiality and privacy of participants were rigorously maintained throughout the research process.

Consent for publication
Not Applicable.

Competing interests
The authors declare no competing interests.

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