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Original Article

Analysis of influencing factors and clinical application of a predictive model for emergence agitation from general anesthesia after abdominal surgery

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Abstract: Objectives: To identify factors influencing emergence agitation (EA) in abdominal surgery patients and develop a predictive model for early clinical intervention. Methods: We retrospectively analyzed data from 794 patients who underwent abdominal surgery between June 2022 and June 2024. Independent risk factors for EA were identified using multivariate logistic regression, which informed the construction of a nomogram model. The dataset was split into a training set (67%) and a validation set (33%), with an additional 119 patients serving as an external validation set. Data analysis was performed using SPSS 26.0 and R 4.3.3, and model performance was assessed using Receiver Operating Characteristic (ROC) and calibration curves. Results: Multivariate analysis revealed nine independent risk factors for EA: age, ASA classification, type of surgery, duration of surgery, intraoperative fluid volume, use of analgesic pumps, catheter usage, postoperative pain, and smoking history. The model's area under the curve (AUC) was 0.787 in the training set, 0.623 in the validation set, and 0.666 in the external validation set, indicating good predictive performance. Calibration curves demonstrated a strong agreement between predicted and observed outcomes, confirming the model's accuracy and consistency. Conclusion: The developed nomogram integrates multiple risk factors to predict EA risk in abdominal surgery patients. It demonstrates high stability and applicability across different datasets, facilitating early identification of high-risk patients and supporting individualized postoperative management.

Keywords: Emergence agitation, risk prediction model, abdominal surgery, logistic regression, cognitive impairment

Introduction

Emergence agitation (EA) is a complex postoperative complication commonly observed during recovery from general anesthesia, characterized by confusion, restlessness, and disorientation [1, 2]. EA compromises patient safety and comfort and poses significant challenges for perioperative management. The incidence of EA varies across different surgical types, with higher rates reported in adults undergoing high-risk surgeries [3]. Specifically, in cases of general anesthesia, the incidence of EA in adult patients ranges from 5% to 20%, influenced by surgical type and intraoperative interventions [4]. Abdominal surgeries, in particular, present a significantly elevated risk of EA due to greater trauma, longer operative times, and substantial physiological burden [5]. Additionally, patients undergoing abdominal surgery often experience intense postoperative pain and stress responses, further increasing the likelihood of EA and complicating postoperative management [6]. Therefore, precise prediction and intervention for EA risk in abdominal surgery patients are crucial.

EA can lead to adverse outcomes, including hemodynamic instability, accidental extubation, spontaneous bleeding, and exacerbated postoperative pain [7]. These complications prolong hospital stays and significantly increase the caregiving burden and healthcare costs [8]. Although the mechanisms underlying EA are not fully understood, it is influenced by various factors, including patient characteristics, type

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of surgery, and anesthesia methods. Additionally, pain, hypoxemia, postoperative delirium, type and dosage of anesthetics, and inadequate intraoperative pain management may contribute to EA [9]. Abdominal surgery, characterized by complex procedures and extensive trauma, often results in more intense postoperative pain and stress responses, thereby increasing the risk of EA. Given these multifaceted causes, predicting and preventing EA remains a challenge in clinical research and practice.

While numerous studies have explored EA risk factors, many focus on specific surgical or pediatric populations, with fewer studies addressing adults, particularly those undergoing abdominal surgery. Existing prediction models often rely on single factors or simplistic approaches, lacking comprehensive analysis. In reality, patients undergoing abdominal surgery face higher EA risks due to prolonged operative times, larger doses of anesthetics, and significant postoperative pain. The lack of a comprehensive prediction tool for EA risk in these patients results in passive postoperative management, limiting opportunities for targeted preoperative and intraoperative interventions.

This study utilizes multivariate logistic regression analysis to identify independent risk factors associated with EA in abdominal surgery patients and constructs a nomogram prediction model. The aim is to provide individualized EA risk assessment and clinical decision support to optimize perioperative management strategies.

Methods and materials

Sample size calculation

To ensure adequate statistical power, we calculated the required sample size based on an estimated EA incidence of 30%. Using the formula $N = Z^2 \times [P \times (1\text{-}P)]/E^2$, where $Z = 1.96$ (for a 95% confidence interval), $P = 0.255$ [10], and $E = 0.05$, the minimum sample size required was approximately 291.

Definition of agitation

EA was assessed using the Riker Sedation-Agitation Scale (SAS) [11], which evaluates agitation levels during emergence from general anesthesia. The SAS ranges from 1 to 7, with higher scores indicating greater agitation. A score of 1 denotes deep sedation, while a score of 7 signifies extreme agitation and dangerous behavior. In this study, scores ≤2 were classified as sedation, a score of 3 as mild agitation, and scores ≥4 as moderate to severe agitation.

Data collection

Data were collected from 794 patients who underwent abdominal surgery between June 2022 and June 2024, in two phases: (1) Internal data (June 2022-June 2023): 675 samples were randomly split into a training set (67%) and a validation set (33%) to ensure scientific validity in model training and initial validation. (2) External validation data (July 2023-June 2024): An additional 119 samples were collected as an external validation set to independently assess model performance across different datasets.

Inclusion Criteria: Patients aged ≥18 years undergoing abdominal surgeries (e.g., hepatobiliary and gastrointestinal procedures), classified as ASA I-III, sedated with dexmedetomidine during surgery, transferred to the post-anesthesia care unit (PACU) with endotracheal intubation, able to communicate, and provided informed consent.

Exclusion Criteria: Patients with psychiatric disorders or organic brain disease, those undergoing abdominal surgery for organ transplantation or plastic surgery, patients requiring emergency interventions due to cardiac arrest, multi-organ failure, or hypovolemic shock, and those involved in other clinical studies or deemed unsuitable by the researcher.

Data collected included: (1) Demographic Characteristics: Age and gender. (2) Clinical Evaluation: ASA classification (I-III) and mental and neurological history (excluding psychiatric or organic brain disease) [12]. (3) Preoperative Factors: Preoperative anxiety (measured using the Amsterdam Preoperative Anxiety and Information Scale [APAIS], with scores ≥11 indicating high anxiety) [13] and benzodiazepine use. (4) Surgical Factors: Surgical site (e.g., hepatobiliary or gastrointestinal), type of surgery, duration, and presence of a urinary catheter. (5) Postoperative Pain: Assessed using the Critical Care Pain Observation Tool (CPOT), with scores > 2 indicating pain [14].

Outcome measures

Primary outcome: Identification of independent risk factors for EA and construction of a nomogram based on these factors.

Secondary outcomes: (1) Assessment of the predictive performance of the constructed model, including AUC, sensitivity, and specificity from ROC analysis. (2) Calibration curve validation for consistency and accuracy across different datasets. (3) External validation set analysis for model robustness. (4) Scoring and EA risk prediction for randomly selected patients to evaluate the model's practical application.

Statistical analysis

All statistical analyses were performed using SPSS 26.0 and R version 4.3.3. Continuous variables were expressed as means ± standard deviations, and categorical variables as frequencies and percentages. Comparisons were made using chi-square tests. To identify independent risk factors for EA, variables were first subjected to univariate analysis. Significant variables were then included in a multivariate logistic regression model. The final regression model was used to construct a nomogram in R for individualized EA risk quantification. Model performance was evaluated using ROC curves and AUC, with sensitivity and specificity calculated to assess discrimination. Calibration curves were utilized to examine the agreement between predicted and actual outcomes, verifying model accuracy and consistency. Both ROC and calibration curves were generated in R, with an external validation set employed for additional robustness testing. Statistical significance was set at $P < 0.05$.

Results

Overall comparison of baseline characteristics

Baseline characteristics were compared across the training, validation, and external validation sets. No significant differences were observed among the groups for key variables, including agitation status (P = 0.483), age (P = 0.476), gender (P = 0.796), ASA classification (P = 0.857), type of surgery (P = 0.653), surgical site (P = 0.740), duration of surgery (P = 0.702), intraoperative blood loss (P = 0.792), intraoperative fluid volume (P = 0.778), use of analgesic pumps (P = 0.643), nerve block application (P = 0.987), catheter use (P = 0.607), preoperative benzodiazepine use (P = 0.891), postoperative pain (P = 0.701), history of diabetes (P = 0.970), history of hypertension (P = 0.997), smoking history (P = 0.591), and preoperative anxiety (P = 0.984) (**Table 1**). These findings indicate consistent baseline characteristics across the groups, providing a balanced foundation for further comparative analysis.

Correlation analysis of baseline variables in the training set

Most correlation coefficients (R values) were below 0.3, indicating low linear correlation among variables and no significant associations. For example, the highest correlation coefficient for age with other variables was only 0.07. Similarly, variables such as gender, type of surgery, and ASA classification exhibited weak correlations. Although intraoperative fluid volume showed slightly higher correlations with other factors, these did not reach clinical significance. Overall, the variables demonstrated strong independence, supporting the use of multivariate analysis (**Figure 1**).

Comparison of baseline characteristics between agitation and non-agitation groups in the training set

Within the training set, baseline characteristics were compared between the agitation and non-agitation groups. Significant differences were identified in age ($P < 0.001$), ASA classification (P = 0.003), type of surgery (P = 0.002), duration of surgery (P = 0.019), intraoperative fluid volume (P = 0.002), analgesic pump use ($P < 0.001$), catheter use ($P < 0.001$), postoperative pain ($P < 0.001$), smoking history ($P < 0.001$), and preoperative anxiety (P = 0.013). No significant differences were found in gender, surgical site, intraoperative blood loss, nerve block application, preoperative benzodiazepine use, history of diabetes, or hypertension between the groups (**Table 2**).

Multivariate logistic regression analysis of independent risk factors for agitation

Multivariate logistic regression identified several independent risk factors for EA. Age (P = 0.001, OR = 0.627, 95% CI: 0.477-0.824) and ASA classification (P = 0.006, OR = 0.662, 95% CI: 0.494-0.888) were associated with a lower risk of agitation. In contrast, type of surgery (P

Table 1. Comparison of baseline characteristics of patients

Variable	Total	validation set (n = 230)	External validation set (n = 119)	Training set (n = 445)	Statistic	*P*-value
Agitation						
Yes	259	68	39	152	1.456	0.483
No	535	162	80	293		
Age					3.515	0.476
< 50	248	78	32	138		
50-60	204	52	30	122		
> 60	342	100	57	185		
Gender					0.457	0.796
Male	664	191	102	371		
Female	130	39	17	74		
ASA classification					1.327	0.857
I	336	101	48	187		
II	294	82	49	163		
III	164	47	22	95		
Type of surgery					0.853	0.653
Minimally invasive	378	110	61	207		
Other	416	120	58	238		
Surgical Site					3.53	0.74
Liver	349	95	55	199		
Intestine	177	58	21	98		
Gallbladder	96	25	17	54		
Other	172	52	26	94		
Duration of surgery					2.186	0.702
< 2 h	301	88	41	172		
2-4 h	323	90	48	185		
> 4 h	170	52	30	88		
Intraoperative blood loss					0.468	0.792
≥ 500 ml	751	218	111	422		
< 500 ml	43	12	8	23		
Intraoperative fluid					1.768	0.778
< 1000 ml	394	112	63	219		
1000-2000 ml	276	79	42	155		
> 2000 ml	124	39	14	71		
Analgesic pump use					0.882	0.643
Yes	367	108	59	200		
No	427	122	60	245		
Nerve block					0.027	0.987
Yes	164	48	25	91		
No	630	182	94	354		
Catheter use					0.999	0.607
Yes	536	159	76	301		
No	258	71	43	144		
Preoperative benzodiazepine use					0.231	0.891
Yes	371	107	58	206		
No	423	123	61	239		

Postoperative pain					0.71	0.701
Yes	232	72	33	127		
No	562	158	86	318		
Diabetes history					0.062	0.97
Yes	90	27	13	50		
No	704	203	106	395		
Hypertension history					0.005	0.997
Yes	135	39	20	76		
No	659	191	99	369		
Smoking history					1.053	0.591
Yes	396	109	63	224		
No	398	121	56	221		
Preoperative anxiety					0.032	0.984
High	97	28	14	55		
Low	697	202	105	390		

Note: ASA classification, American Society of Anesthesiologists classification.

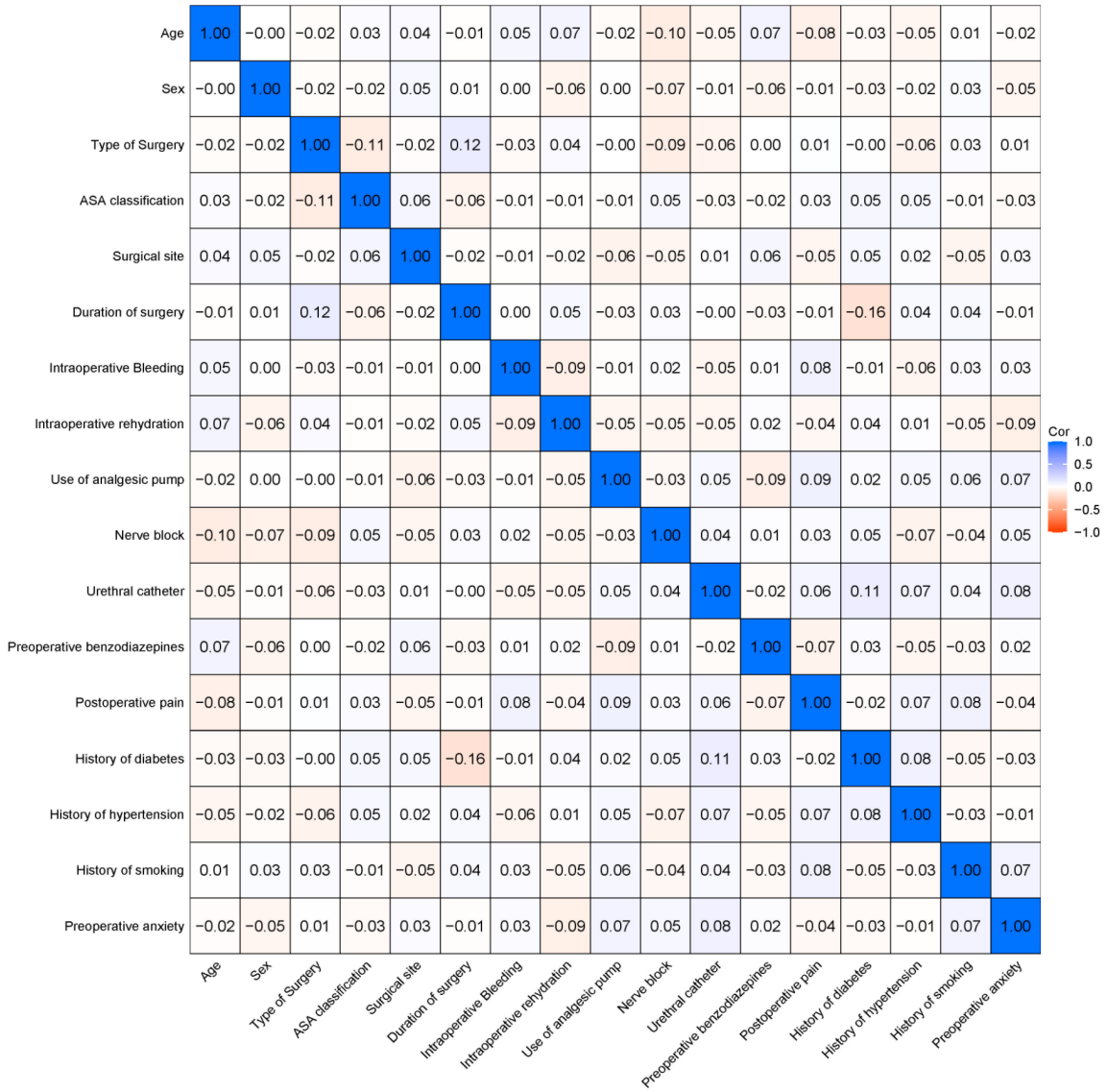

Figure 1. Correlation analysis of baseline characteristics for patients. Note: ASA classification, American Society of Anesthesiologists classification.

Table 2. Comparison of baseline characteristics between agitation and non-agitation groups in the training set

Variable	Total	agitation group (n = 152)	Non-agitation group (n = 293)	Statistic	*P*-value
Age				15.865	< 0.001
< 50	138	29	109		
50-60	122	46	76		
> 60	185	77	108		
Gender				1.318	0.251
Male	371	131	240		
Female	74	21	53		
ASA classification				11.601	0.003
I	187	53	134		
II	163	53	110		
III	95	46	49		
Type of surgery				9.395	0.002
Minimally invasive	207	86	121		
Other	238	66	172		
Surgical Site				3.981	0.264
Liver	199	62	137		
Intestine	98	37	61		
Gallbladder	54	15	39		
Other	94	38	56		
Duration of surgery				8.591	0.014
< 2 h	172	46	126		
2-4 h	185	67	118		
> 4 h	88	39	49		
Intraoperative blood loss				0.149	0.699
≥ 500 ml	422	145	277		
< 500 ml	23	7	16		
Intraoperative fluid				12.378	0.002
< 1000 ml	219	65	154		
1000-2000 ml	155	50	105		
> 2000 ml	71	37	34		
Analgesic pump use				17.278	< 0.001
Yes	200	89	111		
No	245	63	182		
Nerve block				0.052	0.82
Yes	91	32	59		
No	354	120	234		
Catheter use				16.805	< 0.001
Yes	301	122	179		
No	144	30	114		
Preoperative benzodiazepine use				0.005	0.942
Yes	206	70	136		
No	239	82	157		

Postoperative pain				22.901	< 0.001
Yes	127	65	62		
No	318	87	231		
Diabetes history				0.433	0.511
Yes	50	15	35		
No	395	137	258		
Hypertension history				0.065	0.799
Yes	76	25	51		
No	369	127	242		
Smoking history				13.661	< 0.001
Yes	224	95	129		
No	221	57	164		
Preoperative anxiety				6.223	0.013
High	55	27	28		
Low	390	125	265		

Note: ASA classification, American Society of Anesthesiologists classification.

Table 3. Independent risk factors for agitation identified by multivariate logistic regression

Variable	β	SD	Chi-Square	*P*-value	OR	95% CI (Lower)	95% CI (Upper)
Age (< 50 = 1, 50-60 = 2, > 60 = 3)	-0.467	0.14	11.187	0.001	0.627	0.477	0.824
ASA classification (I = 1, II = 2, III = 3)	-0.412	0.15	7.581	0.006	0.662	0.494	0.888
Type of Surgery (Minimally invasive = 1, Other = 2)	0.671	0.232	8.367	0.004	1.956	1.242	3.083
Duration of surgery (< 2 h = 1, 2-4 h = 2, > 4 h = 3)	0.395	0.161	6.011	0.014	1.484	1.082	2.035
Intraoperative fluid (< 1000 ml = 1, 1000-2000 ml = 2, > 2000 ml = 3)	-0.358	0.153	5.487	0.019	0.699	0.518	0.943
Analgesic pump use (Yes = 1, No = 2)	0.808	0.23	12.365	< 0.001	2.244	1.43	3.521
Catheter use (Yes = 1, No = 2)	0.893	0.261	11.741	0.001	2.443	1.466	4.072
Postoperative pain (Yes = 1, No = 2)	1.01	0.25	16.338	< 0.001	2.746	1.682	4.48
Smoking history (Yes = 1, No = 2)	0.703	0.231	9.214	0.002	2.019	1.283	3.178
Preoperative anxiety (High = 1, Low = 2)	0.588	0.344	2.921	0.087	1.801	0.917	3.535
Constant	-4.909	1.188	17.067	< 0.001	0.007		

Note: ASA classification, American Society of Anesthesiologists classification.

= 0.004, OR = 1.956, 95% CI: 1.242-3.083), duration of surgery (P = 0.014, OR = 1.484, 95% CI: 1.082-2.035), intraoperative fluid volume (P = 0.019, OR = 0.699, 95% CI: 0.518-0.943), analgesic pump use (P < 0.001, OR = 2.244, 95% CI: 1.43-3.521), catheter use (P = 0.001, OR = 2.443, 95% CI: 1.466-4.072), postoperative pain (P < 0.001, OR = 2.746, 95% CI: 1.682-4.480), and smoking history (P = 0.002, OR = 2.019, 95% CI: 1.283-3.178) were significant risk factors for agitation. Preoperative anxiety approached significance (P = 0.087, OR = 1.801, 95% CI: 0.917-3.535) but was not statistically significant. These factors provide a reference for predicting EA risk (see **Table 3**).

Nomogram for EA risk prediction

Based on the identified risk factors, we developed a nomogram incorporating nine variables. Strongly associated factors, including postoperative pain, catheter use, and analgesic pump use, had wider scoring ranges and were key predictors of EA. Moderately associated factors, including smoking history, surgery duration, and intraoperative fluid volume, contributed valuable predictive information with less impact on the total score. Weakly associated factors, such as age, ASA classification, and type of surgery, had smaller scoring ranges but still provided predictive value. This nomogram enables clinicians to visualize the relative influence of each variable on EA risk (**Figure 2**).

ROC and calibration curve analysis for the prediction model

The prediction model was validated using ROC and calibration curves. The training set achieved an AUC of 0.787, with a sensitivity of 0.717

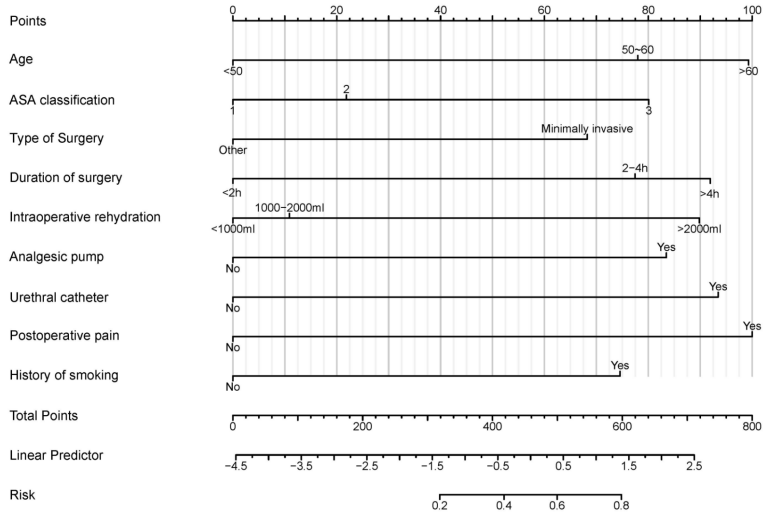

Figure 2. Diagnostic nomogram for EA risk. This figure illustrates the nomogram based on independent risk factors identified in the study, enabling clinicians to quantify and assess individual EA risk levels in abdominal surgery patients. Note: EA, emergence agitation.

and specificity of 0.727, indicating high predictive performance. The validation set and external validation set had AUCs of 0.623 and 0.666, respectively, suggesting moderate predictive capacity across different datasets (see **Figure 3**). Calibration curves demonstrated a strong agreement between predicted probabilities and actual outcomes across all datasets, with mean absolute errors (MAE) of 0.033, 0.013, and 0.037 for the training, validation, and external validation sets, respectively, confirming the model's accuracy and consistency (see **Figure 4**).

Nomogram model scoring and risk comparison between randomly selected non-agitation and agitation patients

Two sample cases were randomly selected to compare EA risk using the nomogram. For a non-agitation patient, the scores were age (48), ASA (48), type of surgery (48), surgery duration (48), intraoperative fluid volume (48), analgesic pump use (48), catheter use (96), postoperative pain (48), and smoking history (87), totaling 519 points and corresponding to a 35% predicted EA risk (see **Figure 5**). In contrast, an agitation patient scored age (98), ASA (48), type of surgery (48), surgery duration (48), intraoperative fluid volume (54), analgesic pump use (48), catheter use (96), postoperative pain (48), and smoking history (87), resulting in a total score of 575 points and a predicted EA risk of 50% (see **Figure 6**).

Discussion

The nomogram predictive model developed in this study demonstrates good accuracy in predicting the risk of emergence agitation (EA) in abdominal surgery patients. Using multivariate logistic regression analysis, we identified age, ASA classification, type of surgery, duration of surgery, intraoperative fluid volume, use of analgesic pumps, catheterization, postoperative pain, and smoking history as independent risk factors for EA. ROC curve analysis on internal and external datasets showed high AUC values, and calibration curves indicated that the predicted probabilities align well with actual outcomes across different datasets. These results support the clinical applicability of the model in predicting EA risk in abdominal surgery patients.

Our study identified nine independent risk factors that play critical roles in the occurrence of EA. Namigar et al. [10] found that older patients (> 60 years) have a higher risk of postoperative EA, likely due to physiological decline, reduced metabolic rate, decreased neurological regulation, and slower anesthetic clearance, which increases the likelihood of awakening complications. Furthermore, Song et al. [15] indicated that ASA classification reflects the patient's health status, with higher classifications often involving cardiovascular or metabolic issues, making these patients more susceptible to physiological stress and hemodynamic instability, thereby increasing EA risk. Lee et al. [16] highlighted the impact of surgical type on EA, noting that traditional open surgeries, involving larger incisions and longer recovery times, lead to stronger postoperative pain and stress responses, resulting in a higher EA risk compared to minimally invasive surgeries, which have lower EA incidence due to lesser physiological disturbance, lighter trauma, and faster recovery. Additionally, Monteiro et al. [17] found that longer surgeries lead to more pronounced cumulative effects of anesthesia and greater body fatigue, contributing to postoperative agitation. Patients undergoing surgeries longer than

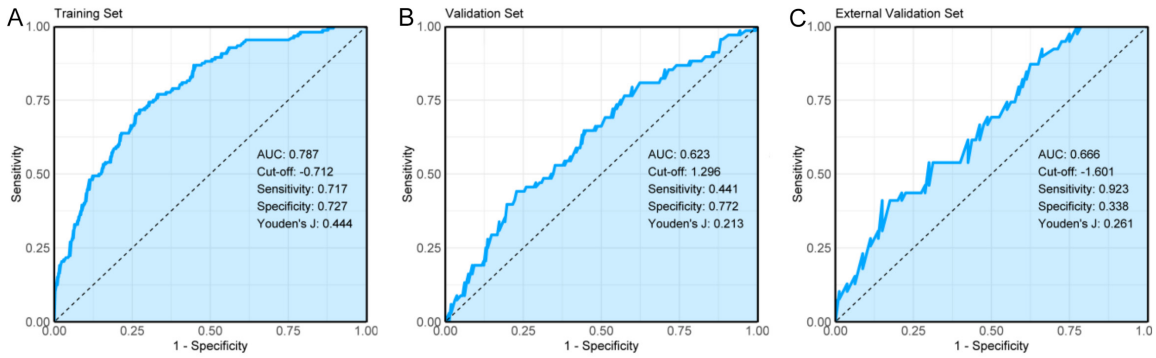

Figure 3. ROC curves of the EA prediction model. A. The ROC curve for the training set with an AUC of 0.787, sensitivity of 0.717, and specificity of 0.727. B. The ROC curve for the validation set with an AUC of 0.623. C. The ROC curve for the external validation set with an AUC of 0.666. Note: ROC, Receiver Operating Characteristic; AUC, Area Under the Curve.

four hours, due to prolonged anesthesia and exposure to trauma, have slower physiological recovery, thus significantly increasing EA risk. Overall, patient age, ASA classification, type of surgery, and duration of surgery are pivotal factors in determining the likelihood of emergence agitation in abdominal surgery patients.

Regarding intraoperative fluid volume, Wei et al. [18] noted that surgeries requiring large fluid volumes often indicate greater surgical complexity and potential blood loss. Excessive fluid volume can lead to postoperative electrolyte imbalance, intensifying discomfort and raising EA risk. Cao et al. [19] found that while analgesic pumps provide continuous pain control in postoperative management, inappropriate dosing or drug selection may lead to uneven analgesic effects, causing agitation during emergence if pain is not effectively relieved. Wegner et al. [20] demonstrated that catheterization causes localized discomfort and a sense of restriction, which can trigger anxiety and agitation during awakening, particularly in patients with prolonged catheterization, who experience stronger repulsion to the foreign object, thereby increasing EA incidence. Wang et al. [21] identified postoperative pain as a direct trigger for EA. Pain not only induces discomfort but also activates the sympathetic nervous system, leading to symptoms such as increased heart rate and blood pressure fluctuations, further aggravating agitation. Effective postoperative pain management is a key measure for preventing EA. Aniley et al. [22] discovered an association between smoking history and EA. Long-term smoking may damage lung function and the cardiovascular system, causing abnormal responses to anesthetics and analgesics, increasing instability during emergence. Additionally, smoking affects the metabolism of anesthetics, leading to hemodynamic fluctuations during emergence, further raising EA risk. These insights emphasize the necessity of optimizing intraoperative fluid management, analgesic strategies, catheter use, pain control, and addressing smoking history to effectively reduce the risk of EA.

This EA predictive model offers a quantitative, individualized risk assessment tool for clinical use, allowing early identification of high-risk patients before or during surgery and providing scientific support for effective intervention measures. Our study results indicate that the model's AUC in the training set reached 0.787, with AUCs of 0.623 and 0.666 in the validation and external validation sets, respectively, suggesting good predictive performance across different datasets, with particularly strong discriminatory power in the training set. Additionally, calibration curve analysis further confirmed the model's accuracy and consistency, showing close alignment between predicted and actual values, with MAEs of 0.033, 0.013, and 0.037 for the training, validation, and external validation sets, respectively. These results indicate the model's robustness and reliability across various scenarios, making it suitable for clinical promotion and application. Similarly, Nagata et al. [23] developed a postoperative delirium (POD) prediction model using machine learning algorithms for cardiovascular surgery patients, with results demonstrating good predictive per-

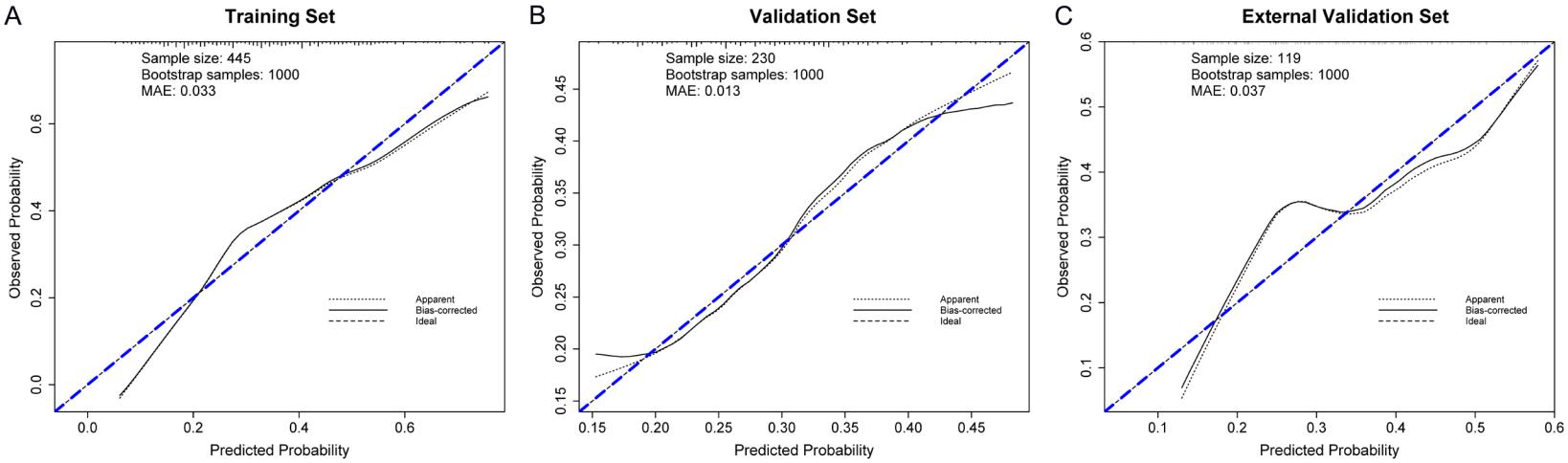

Figure 4. Calibration curves for the prediction model across different data sets. A. The calibration curve for the training set with a MAE of 0.033. B. The calibration curve for the validation set with an MAE of 0.013. C. The calibration curve for the external validation set with an MAE of 0.037. Note: MAE, Mean Absolute Error.

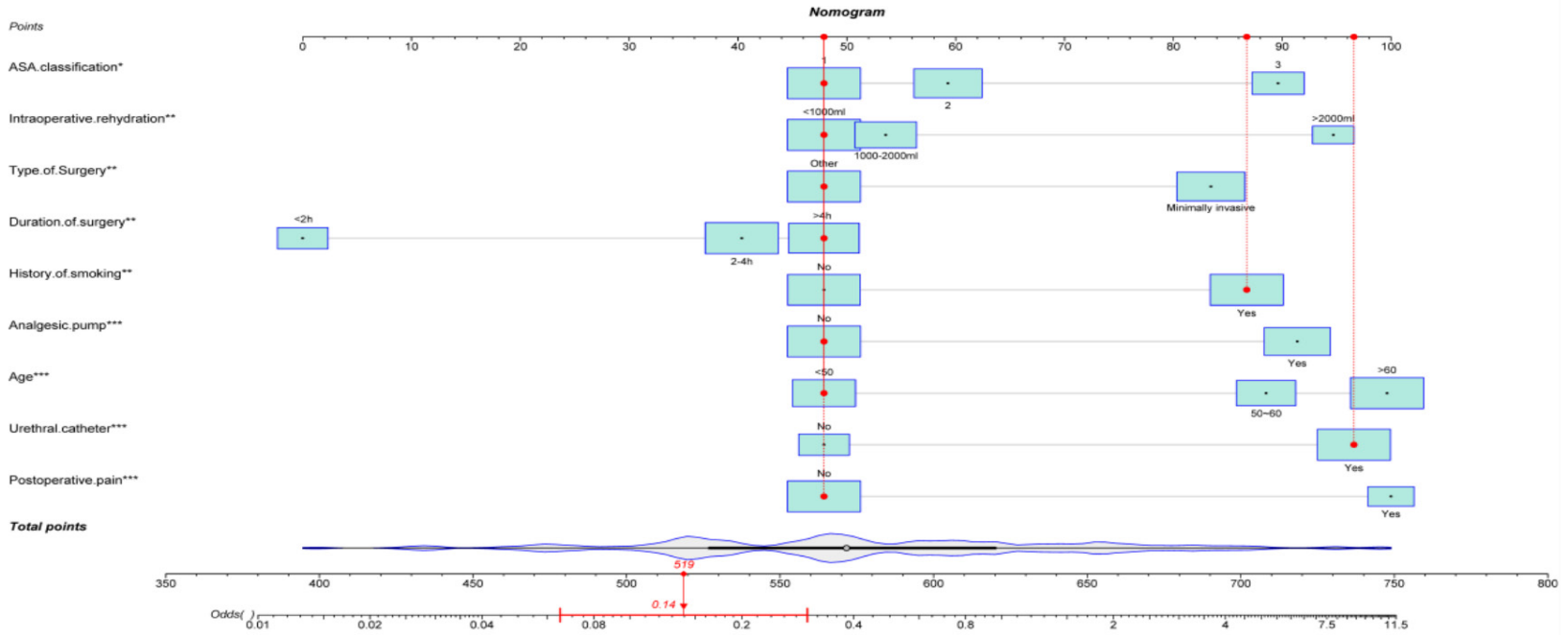

Figure 5. Nomogram score for a randomly selected non-agitation patient. This figure displays the nomogram score for a patient without EA, illustrating the cumulative impact of each risk factor and the associated risk probability for EA. Note: EA, emergence agitation.

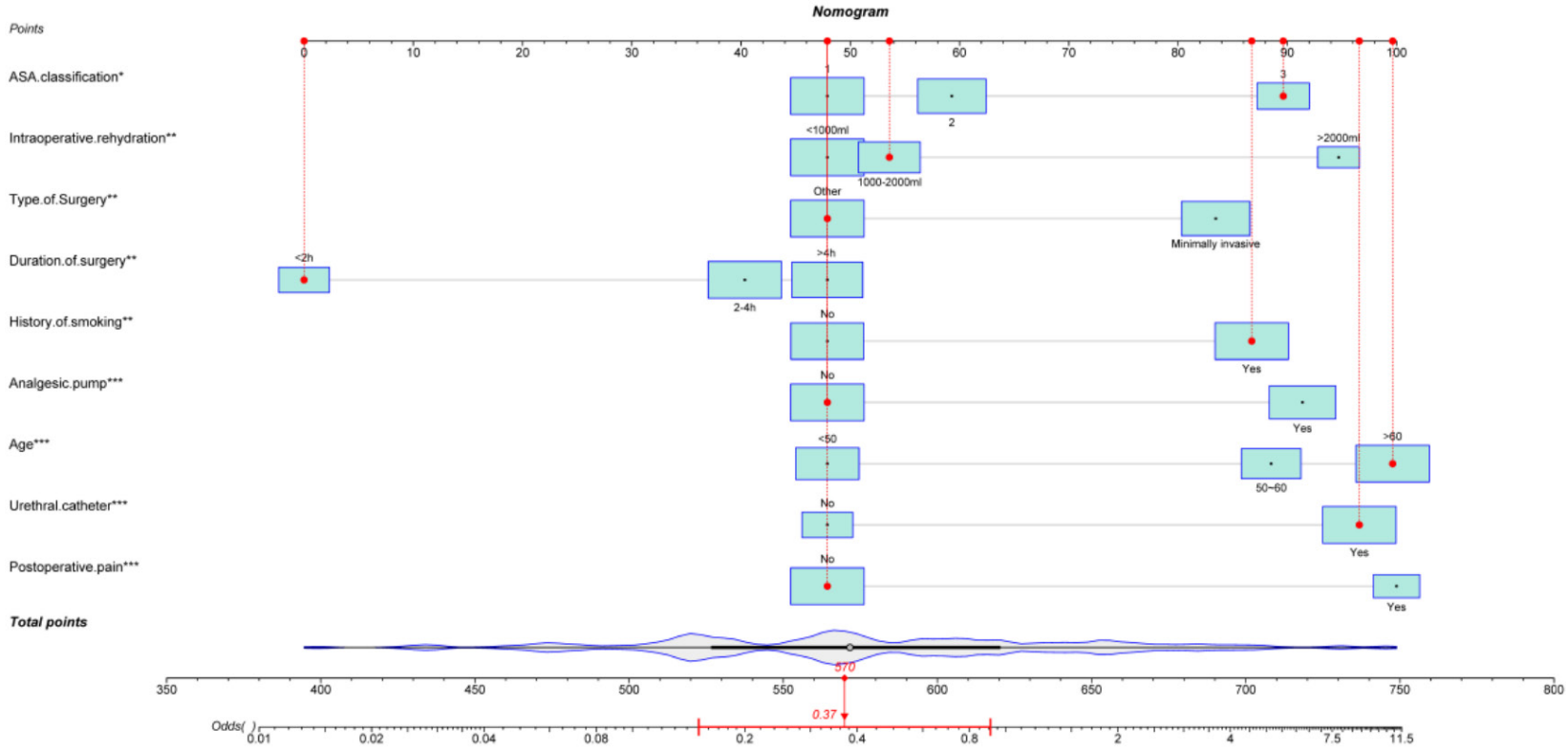

Figure 6. Nomogram score for a randomly selected agitation patient. This figure shows the nomogram score for a patient who experienced EA, with the corresponding cumulative score and predicted EA risk probability. Note: EA, emergence agitation.

formance across different datasets, supporting the potential of machine learning methods in postoperative complication prediction. Furthermore, Song et al. [24] constructed a POD prediction model for elderly hip fracture patients using machine learning algorithms and SHapley Additive exPlanations, further validating the effectiveness of multifactorial models in complex clinical settings. Li et al. [25] applied a random forest algorithm to construct a POD prediction model for heart valve surgery patients, showcasing the advantages of multifactorial machine learning models in clinical prediction and supporting the design concept of this study's model. Collectively, these findings validate the robustness and applicability of our predictive model, while also highlighting the potential of machine learning algorithms in enhancing the accuracy of postoperative complication predictions in clinical practice.

The application of this model is significant for the precision of perioperative management, especially in providing valuable references for personalized intervention. Based on the model's high-risk identification, clinicians can develop targeted anesthesia and postoperative analgesia plans before surgery and enhance postoperative care for high-risk patients, maximizing the reduction of EA incidence, improving perioperative resource utilization efficiency, and reducing patient management burden. Although the model is primarily aimed at abdominal surgery patients, the variables included are broadly applicable to other surgical types, indicating the model's potential for expansion to other surgery types and patient populations. In the future, larger-scale multicenter validation studies will further expand the model's applicability, optimizing postoperative management strategies and achieving significant clinical value in improving patient outcomes and medical resource allocation. Overall, the model significantly enhances the precision of perioperative management and holds potential for broader application across various surgical populations.

Despite the high accuracy and consistency of this EA predictive model, there are some limitations. First, the sample's racial and cultural background constraints may limit the model's broad applicability. Additionally, potential variables, such as drug metabolism characteristics and individual physiological differences, were not included, which may affect the model's predictive effectiveness. The mechanisms underlying EA are complex and involve various neurobiological factors, and the current model does not fully cover these aspects. To improve the model's applicability, future research could further validate the model in larger, multicenter studies and incorporate more intraoperative monitoring and physiological data to enhance the model's precision and dynamic predictive capabilities. Additionally, incorporating metabolic characteristics and genetic polymorphisms will help refine EA risk assessment. Ultimately, ongoing optimization of the model through application research in real clinical processes will promote its widespread use in perioperative management. Addressing these limitations in future studies will further enhance the model's applicability and precision in clinical settings.

In conclusion, this study developed a predictive model for EA risk in abdominal surgery patients through multifactorial analysis. The nomogram-based model enables clinicians to quickly and intuitively conduct individualized risk assessments. Validation results across multiple datasets indicate that the model has high applicability and robustness among abdominal surgery patients, providing scientific support for early identification and prevention of EA.

Disclosure of conflict of interest

None.

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References

[1] Tolly B, Waly A, Peterson G, Erbes CR, Prielipp RC and Apostolidou I. Adult emergence agitation: a veteran-focused narrative review. Anesth Analg 2021; 132: 353-364.

[2] Duan J, Ju X, Wang X, Liu N, Xu S and Wang S. Effects of remimazolam and propofol on emergence agitation in elderly patients undergoing hip replacement: a clinical, randomized, controlled study. Drug Des Devel Ther 2023; 17: 2669-2678.

[3] Lee S, Sohn JY, Hwang IE, Lee HJ, Yoon S, Bahk JH and Kim BR. Effect of a repeated verbal re-

minder of orientation on emergence agitation after general anaesthesia for minimally invasive abdominal surgery: a randomised controlled trial. Br J Anaesth 2023; 130: 439-445.
[4] Li T, Li J, Yuan L, Wu J, Jiang C, Daniels J, Mehta RL, Wang M, Yeung J, Jackson T, Melody T, Jin S, Yao Y, Wu J, Chen J, Smith FG and Lian Q. Effect of regional vs general anesthesia on incidence of postoperative delirium in older patients undergoing hip fracture surgery: the RAGA randomized trial. JAMA 2022; 327: 50-58.
[5] Shen X, Yu H, Chen K, Xue Q, Lu J and Xie Z. Association between severe preoperative hearing impairment and postoperative emergence agitation among elderly patients undergoing middle ear surgery. J Clin Anesth 2023; 91: 111254.
[6] Yan F, Yuan LH, He X and Yu KF. Correlation between pre-anesthesia anxiety and emergence agitation in non-small cell lung cancer surgery patients. World J Psychiatry 2024; 14: 930-937.
[7] Gentili ME, Gnaho A and Musellec H. Postoperative agitation on emergence of general anesthesia revealing former post-traumatic stress disorder. Rev Neurol (Paris) 2017; 173: 172-173.
[8] Zhang M, Wang B and Mao W. Effect of different anesthesia methods on emergence agitation and related complications in postoperative patients with osteosarcoma. J Healthc Eng 2021; 2021: 7120035.
[9] Zhang X, Qi S, Lin Z, Zhang Y, Dai W, Tian W, Tian J, Zheng L, Su D and Huai X. Pre-operative administration of butorphanol mitigates emergence agitation in patients undergoing functional endoscopic sinus surgery: a randomized controlled clinical trial. Front Psychiatry 2022; 13: 1090149.
[10] Namigar T, Serap K, Esra AT, Özgül O, Can Ö A, Aysel A and Achmet A. The correlation among the ramsay sedation scale, richmond agitation sedation scale and riker sedation agitation scale during midazolam-remifentanil sedation. Rev Bras Anestesiol 2017; 67: 347-354.
[11] Shivali S and Thiagarajan P. A practical guide to the american society of anesthesiologists-physical status classification (ASA-PS). Indian J Anaesth 2022; 66: 299-300.
[12] Ayele B, Tadesse M, Tilahun R and Nega B. Translation of the amsterdam preoperative anxiety and information score (APAIS) into the amharic version and its validation for evaluation of preoperative anxiety. Ethiop J Health Sci 2021; 31: 349-358.
[13] Shahid A, Owen VS, Sept BG, Longmore S, Soo A, Brundin-Mather R, Krewulak KD, Moss SJ, Plotnikoff KM, Gélinas C, Fiest KM and Stelfox HT. Study protocol: development and pilot testing of the critical care pain observation tool for families (CPOT-Fam). Pilot Feasibility Stud 2022; 8: 147.
[14] Yu L, Wang B, Huang L and Ni L. Analysis of contributing factors and nursing interventions for postoperative agitation following general anesthesia in thoracotomy patients. Medicine (Baltimore) 2024; 103: e39580.
[15] Song SS, Lin L, Li L and Han XD. Influencing factors and risk prediction model for emergence agitation after general anesthesia for primary liver cancer. World J Gastrointest Surg 2024; 16: 2194-2201.
[16] Lee SJ and Sung TY. Emergence agitation: current knowledge and unresolved questions. Korean J Anesthesiol 2020; 73: 471-485.
[17] Monteiro JN, Dhokte NS and Goraksha SU. A prospective observational single center study evaluating emergence agitation in the early postoperative period in adult patients undergoing elective craniotomies under general anesthesia. J Anaesthesiol Clin Pharmacol 2023; 39: 25-30.
[18] Wei B, Feng Y, Chen W, Ren D, Xiao D and Chen B. Risk factors for emergence agitation in adults after general anesthesia: a systematic review and meta-analysis. Acta Anaesthesiol Scand 2021; 65: 719-729.
[19] Cao L, Ren Y, Wen F, Du J, He M and Huang H. Research trends related to emergence agitation in the post-anaesthesia care unit from 2001 to 2023: a bibliometric analysis. Open Med (Wars) 2024; 19: 20241021.
[20] Wegner GRM, Wegner BFM, Oliveira HG, Costa LA, Spagnol LW, Spagnol VW and de Oliveira Filho GTF. Pharmacological and non-pharmacological interventions in patients undergoing nasal surgeries for prevention of emergence agitation: a systematic review and network meta-analysis. Braz J Anesthesiol 2024; 75: 844565.
[21] Wang N, Hao J, Zhang J, Du J and Luo Z. Risk factors for emergence agitation during the awakening period in elderly patients after total joint arthroplasty: a retrospective cohort study. BMJ Open 2023; 13: e068284.
[22] Aniley HT, Mekuria ST, Kebede MA, Gebreanania AH, Muleta MB and Aniley TT. Magnitude of emergence agitation, its interventions and associated factors among paediatric surgical patients. BMC Anesthesiol 2024; 24: 236.
[23] Nagata C, Hata M, Miyazaki Y, Masuda H, Wada T, Kimura T, Fujii M, Sakurai Y, Matsubara Y, Yoshida K, Miyagawa S, Ikeda M and Ueno T. Development of postoperative delirium prediction models in patients undergoing cardio-

vascular surgery using machine learning algorithms. Sci Rep 2023; 13: 21090.
[24] Song Y, Zhang D, Wang Q, Liu Y, Chen K, Sun J, Shi L, Li B, Yang X, Mi W and Cao J. Prediction models for postoperative delirium in elderly patients with machine-learning algorithms and SHapley additive exPlanations. Transl Psychiatry 2024; 14: 57.
[25] Li Q, Li J, Chen J, Zhao X, Zhuang J, Zhong G, Song Y and Lei L. A machine learning-based prediction model for postoperative delirium in cardiac valve surgery using electronic health records. BMC Cardiovasc Disord 2024; 24: 56.