Development and Validation of a LASSO-Based Prediction Model for Postoperative Bleeding Following Pediatric Tonsillectomy and Adenoidectomy

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AIM: Despite technological advancements, children undergoing adenotonsillectomy using low-temperature plasma radiofrequency ablation remain at risk for postoperative bleeding. This study aimed to construct a precise machine learning-based model to predict the risk of postoperative bleeding in this population.

METHODS: A retrospective cohort study involving 306 pediatric patients who underwent the procedure between January 2023 and January 2025 was conducted. Clinical data, including demographic characteristics, preoperative laboratory findings, and surgical details, were collected and cleaned. The dataset was randomly divided into a training set (n = 244) and a validation set (n = 62) at an 8:2 ratio. A predictive model was developed using the least absolute shrinkage and selection operator (LASSO) cross-validation algorithm, and its performance was assessed in the validation cohort.

RESULTS: Among 306 children, 24 (7.8%) experienced postoperative bleeding. Univariate comparisons identified significant differences in 11 variables: age, height, weight, body mass index (BMI), disease duration, postoperative infection, dietary compliance, postoperative pain, lymphocyte count, neutrophil-to-lymphocyte ratio (NLR), and neutrophil-to-platelet ratio (NPR) (all $p < 0.05$). At lambda.1se = 0.022, LASSO logistic regression retained four predictors: postoperative infection, dietary compliance, age, and postoperative pain. After 1000 bootstrap resamples, the out-of-bag area under the curve (AUC) was 0.935 (95% CI: 0.875–0.995), with a Brier score of 0.035, calibration intercept of 0.045, and calibration slope of 1.418. At the optimal probability cutoff of 0.114, sensitivity was 0.875, specificity was 0.936, and the Youden index was 0.811.

CONCLUSIONS: Postoperative infection, dietary adherence, postoperative pain, and age are significant predictors of bleeding following pediatric adenotonsillectomy using low-temperature plasma radiofrequency ablation. The LASSO-based model provides a reliable tool for identifying high-risk patients and optimizing perioperative management.

Keywords: pediatric patients; tonsillectomy; adenotonsillectomy; postoperative bleeding; least absolute shrinkage and selection operator regression; machine learning

Introduction

Low-temperature plasma radiofrequency ablation has become a standard surgical modality for managing chronic tonsillitis, adenoid hypertrophy, and related obstructive sleep disorders in pediatric patients, reflecting the ongoing evolution of surgical technology [1]. This technique utilizes ionized energy at temperatures of 40–70 °C to ablate tissue, thereby reducing the need for compressive hemostasis. When combined with intraoperative hemostatic interventions, the safety profile of this procedure is markedly superior to that of conventional electrocautery [2]. However, complete wound healing typically takes 2 to 3 weeks, during which both primary and secondary postoperative bleeding can occur. With an incidence of approximately 5% to 10%, postoperative bleeding remains one of the most common complications of tonsillectomy and adenoidectomy and can significantly impact recovery quality [3,4]. Compared with adults, postoperative care in pediatric patients presents unique challenges, making timely evaluation of high-risk individuals essential for tailoring perioperative management and minimizing hemorrhagic complications.

Current research on adenotonsillectomy using low-temperature plasma radiofrequency ablation has largely focused on the underlying causes of bleeding. To date, no validated model exists for postoperative bleeding risk assessment in pediatric patients undergoing this procedure. There is a critical need to develop effective predictive tools to facilitate timely clinical intervention.

With the rapid advancements in machine learning (ML) technology, its applications in medicine—particularly in

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outcome prediction and clinical decision support—are increasingly promising [5,6,7]. In this study, we employed the least absolute shrinkage and selection operator (LASSO) algorithm with cross-validation to establish a predictive model for postoperative bleeding in children undergoing adenotonsillectomy using low-temperature plasma radiofrequency ablation. This model aims to provide an accurate and efficient tool for identifying high-risk patients and supporting evidence-based strategies for improving surgical safety and recovery in pediatric care.

Methods

Study Population

This retrospective cohort study included 306 pediatric patients who underwent adenotonsillectomy using low-temperature plasma radiofrequency ablation at Anhui Children's Hospital, between January 2023 and January 2025. Age, sex, surgery duration, and other clinical characteristics were evaluated as candidate predictors. All consecutive patients who met the predefined eligibility criteria during the study period were included to minimize selection bias.

Inclusion criteria included: (1) patients aged 2 to 18 years; (2) a confirmed diagnosis of tonsillitis, tonsillar hypertrophy, or obstructive sleep apnea-hypopnea syndrome (OSAHS) based on comprehensive pathological and imaging evaluations, with an indication for surgical intervention; (3) all patients underwent adenotonsillectomy using low-temperature plasma radiofrequency ablation; (4) complete clinical documentation was available, including preoperative assessment, intraoperative parameters, and postoperative follow-up data.

Exclusion criteria included: (1) known coagulation disorders or preoperative use of anticoagulant therapy; (2) concurrent acute infection, significant hepatic, renal, or cardiac insufficiency, or autoimmune disease; (3) incomplete medical records or loss to follow-up; (4) presence of other major organic or immunological disorders.

This study was conducted in accordance with the principles of the Declaration of Helsinki and received approval from the Ethics Committee of Anhui Children's Hospital (Approval Number: EYLL-2026-038). No patient-identifiable information was disclosed beyond the scope of the data analyses performed in this study. Because this was a retrospective study using de-identified clinical data, the requirement for written informed consent was waived by the Ethics Committee of Anhui Children's Hospital.

Surgical Procedure

All pediatric patients underwent comprehensive preoperative assessments and received adenotonsillectomy using low-temperature plasma radiofrequency ablation, performed by experienced lead surgeons. The procedure utilized a plasma surgical system (low-temperature plasma surgical system, BONSS, model: BDS621; energy setting: 7–8), with physiological saline as the conductive medium. The tonsils were dissected along the peritonsillar capsule and completely removed. Under nasal endoscopic visualization, the adenoid tissue was completely ablated. The specific criteria for determining adequate removal included the clear and complete exposure of the posterior pharyngeal wall fascial plane, unobstructed visualization of bilateral choanae without any residual obstructing lymphoid tissue, and the strict preservation of tissue surrounding the torus tubarius to prevent Eustachian tube dysfunction.

Postoperatively, patients received intravenous antibiotics for 1 to 5 days, depending on recovery progress. During the 3 weeks after surgery, the occurrence of postoperative bleeding was monitored and documented.

In the event of postoperative bleeding, measures were taken to minimize patient agitation and crying. The tonsillar bed was assessed for active bleeding, and the pharyngeal wall was examined for retrograde blood flow from the nasopharynx. If no active bleeding was detected, local cold compresses and intravenous hemostatic agents were used. Mild oozing was managed by compression. In cases of active bleeding or failure of conservative measures, ligation or bipolar electrocoagulation was promptly performed.

Clinical Data Collection

Clinical data were collected in accordance with the inclusion and exclusion criteria and under the hospital's medical records management protocols via the electronic medical record system. Postoperative variables, including infection, pain, and dietary compliance, were extracted from medical and nursing records documented during the early postoperative period (typically days 1 to 5). Postoperative infection was identified from the electronic medical records based on a physician-documented diagnosis of infection during the postoperative period. The diagnostic criteria included fever (body temperature ≥38.0 °C) accompanied by elevated inflammatory indicators, such as white blood cell count and C-reactive protein, and/or local signs of infection, for which antimicrobial treatment was initiated. Infection assessments covered the postoperative hospital stay (days 1–5) and documented follow-up within 3 weeks after surgery. Due to the retrospective design of this study, the precise hourly sequence between these postoperative assessments and the onset of bleeding was not consistently recorded. Consequently, strict temporal precedence cannot be definitively guaranteed for all patients, and potential reverse causation or information leakage cannot be entirely excluded. The following categories of data were extracted:

(1) Demographic and baseline clinical characteristics: including age, sex, height, weight, duration of illness, tonsil infiltration degree, and prior medical history.

(2) Preoperative assessment data: encompassing imaging studies and laboratory parameters [white blood cell count (WBC), neutrophil count (NEUT#), lymphocyte count (LYMPH#), monocyte count (MONO#), platelet

count (PLT), and calculated indices such as neutrophil-to-lymphocyte ratio (NLR), platelet-to-lymphocyte ratio (PLR), systemic immune-inflammation index (SII), neutrophil-to-platelet ratio (NPR), and lymphocyte-to-monocyte ratio (LMR)].

(3) Surgical data: including operative time, presence of postoperative infection, effectiveness of postoperative education, postoperative pain levels, dietary compliance, postoperative hospital stay, and incidence of postoperative bleeding.

(4) Postoperative bleeding: Bleeding episodes occurring within 3 weeks after surgery were recorded. Post-discharge bleeding events occurring on postoperative days 8–21 were ascertained through structured telephone follow-up conducted by the surgical team at postoperative weeks 1, 2, and 3, as well as a review of outpatient, emergency department, and readmission records at Anhui Children's Hospital. At discharge, caregivers were instructed to contact the hospital immediately if any oral or nasal bleeding occurred. Postoperative bleeding was defined as documented oral or nasal bleeding originating from the surgical site after adenotonsillectomy using low-temperature plasma radiofrequency ablation that required operative intervention. It was analyzed as a binary outcome: 0 = no bleeding and 1 = bleeding.

Data Preprocessing and Variable Coding

Records were screened for duplicate patient identifiers. Potential outliers were identified using the 1.5-interquartile-range rule and verified against the original medical records; clinically plausible extreme values were retained. No missing values were found among the variables included in the analysis (0/306, 0%); therefore, no imputation or variable exclusion was performed. Dietary adherence, effectiveness of postoperative education, and postoperative pain were assessed using postoperative nursing and follow-up records. Dietary adherence was graded as good when the recommended cool or room-temperature soft diet was consistently followed, moderate when occasional deviations were documented, and poor when repeated nonadherence or premature intake of hard, hot, or irritating foods was documented. The effectiveness of postoperative education was graded as good when the child or caregiver understood and followed the principal postoperative instructions, moderate when repeated reminders were required, and poor when key instructions were not understood or followed. Both variables were coded as 1 = poor, 2 = moderate, and 3 = good. Postoperative pain was coded as 0 = absent and 1 = present according to the nursing or follow-up records. Postoperative pain was assessed daily during the postoperative hospital stay (typically postoperative days 1–5) by ward nurses and attending physicians. Pain was evaluated based on the children's self-reports and behavioral observations, including persistent crying, refusal to swallow or eat, and sleep disturbance. Any documented pain-related manifestation during the early postoperative period was coded as pain present (1), whereas the absence of any such record was coded as pain absent (0).

Predictive Model Development

(1) Dataset partitioning: The dataset was randomly split into a training set (80%) and a validation set (20%) for the purpose of model training and validation.

(2) Predictor selection and data preprocessing: To rigorously prevent potential information leakage, all variable selection, data preprocessing, and model development procedures were performed exclusively within the training set. Candidate variables were selected based on the univariate analysis results and entered into the LASSO analysis for further variable selection. Prior to modeling, continuous variables were standardized using the Z-score method to ensure scale uniformity. Categorical variables were transformed into numerical formats using dummy coding strategies. Subsequently, the LASSO regression algorithm, implemented using the "glmnet" package in R (version 4.2.3; R Foundation for Statistical Computing, Vienna, Austria), was applied to the preprocessed training data to identify significant predictors of postoperative bleeding risk following adenotonsillectomy using low-temperature plasma radiofrequency ablation.

(3) Model training: Variables with zero regression coefficients were excluded through dimensionality reduction. Ten-fold cross-validation was conducted to determine the final variables included in the diagnostic model. A risk prediction model was subsequently established based on the LASSO-selected predictors.

(4) Correlation analysis among predictors: Spearman's correlation coefficients were calculated to examine the relationships among the identified predictors and assess potential multicollinearity, thereby refining the final selection of variables for inclusion in the predictive model.

Statistical Analysis and Model Evaluation

All statistical analyses were performed using R software (version 4.2.3, R Foundation for Statistical Computing, Vienna, Austria). Categorical variables were presented as frequencies and percentages [n (%)] and compared using the chi-square test or Fisher's exact test, with a two-sided significance level of $\alpha = 0.05$. Continuous variables that did not follow a normal distribution were reported as medians and interquartile ranges [M(P25, P75)] and analyzed using the Mann-Whitney U test. Normally distributed continuous data were expressed as mean ± standard deviation and compared using independent-samples *t*-tests.

LASSO logistic regression was implemented using the glmnet package with a binomial distribution, $\alpha = 1$, and 10-fold cross-validation. Cross-validated binomial deviance was used to select λ. Both lambda.min and lambda.1se were examined, and lambda.1se was selected for the final model to improve parsimony and reduce overfitting. Receiver operating characteristic (ROC) curves were generated us-

ing the "pROC" package (version 1.19.1), and key performance metrics—including area under the curve (AUC), sensitivity, specificity, accuracy, Youden index, and optimal threshold—were calculated to evaluate model performance. The final four-predictor model was internally validated in the full cohort using 1000 bootstrap resamples. Calibration was assessed using bootstrap out-of-bag predictions, a calibration curve, calibration intercept, calibration slope, and Brier score. The ideal values of the calibration intercept and slope were 0 and 1, respectively. The optimal probability cutoff was determined by maximizing the Youden index. Statistical significance was defined as a two-sided *p*-value less than 0.05.

Results

Dataset Division and Baseline Characteristics

A total of 306 pediatric patients who underwent adenotonsillectomy using low-temperature plasma radiofrequency ablation were enrolled in this study. The dataset was randomly divided into a training set (n = 244) and a validation set (n = 62) at an 8:2 ratio and a fixed random seed of 3. The training and validation cohorts differed significantly in operative time ($p = 0.017$), monocyte count ($p = 0.002$), and postoperative pain ($p = 0.021$), whereas no statistically significant differences were observed in the remaining characteristics (Table 1).

Baseline Characteristics Comparison Between Bleeding and Non-Bleeding Groups in the Training Set

The Shapiro-Wilk test, performed using the compareGroups package, was employed to assess the normality of continuous variables. As all variables deviated from a normal distribution, the Mann-Whitney U test was used for group comparisons. Categorical variables were analyzed using the chi-square test or Fisher's exact test, as appropriate.

As summarized in Table 2, significant differences ($p < 0.05$) were observed between the bleeding and non-bleeding groups in terms of age, height, weight, body mass index (BMI), duration of illness, postoperative infection, dietary compliance, postoperative pain, lymphocyte count and NLR; NPR was significantly higher in the bleeding group than in the non-bleeding group ($p = 0.042$).

LASSO Logistic Regression Model Construction in the Training Set

The LASSO regression analysis identified a λ value of 0.005 as yielding the lowest cross-validated binomial deviance, resulting in a model comprising eight variables: postoperative infection, dietary compliance, effectiveness of postoperative education, postoperative pain, age, body mass index (BMI), disease duration (in months), and NLR (Fig. 1A,B, Table 3).

To enhance model parsimony, the one-standard-error rule was applied, identifying λ = 0.022 as optimal. This more streamlined model retained four core predictors: postoperative infection, dietary compliance, age, and postoperative pain (Fig. 1A,B, Table 3). To facilitate clinical application, individual postoperative bleeding risk was calculated using the inverse logit transformation of the linear predictor (log-odds). This predictor was computed by summing the model's intercept (–7.106) with the products of the variables and their LASSO coefficients (postoperative infection: 3.36, dietary compliance: –0.88, postoperative pain: 1.70, age: 0.46). The optimal prediction threshold was 0.114 (Youden index: 0.811), above which patients were classified as high-risk.

Correlation Analysis of Predictive Variables

Spearman correlation analysis was performed among the four predictors retained by the LASSO model. Most pairwise correlations were statistically significant; however, the correlation between postoperative infection and postoperative pain did not reach statistical significance (r = 0.13, $p = 0.05$). All absolute correlation coefficients were below 0.7, indicating no strong pairwise correlations among the predictors (Fig. 1C and Table 4).

Predictive Performance Evaluation of the Cross-Validation Model

The predictive performance of the LASSO-derived model (M4) was evaluated using ROC curve analysis, and the optimal cutoff value for each predictor was determined by maximizing the Youden index. In the training set, model M4 achieved an AUC of 0.96, with a sensitivity of 0.95, a specificity of 0.87, and an overall accuracy of 0.88 (Fig. 2A, Table 5).

Validation of the Predictive Model

The performance of the LASSO-derived model (M4) was further validated in the validation set using ROC curve analysis. The Youden index and optimal cutoff values for each predictor were automatically determined. In the validation set (n = 62), model M4 achieved an AUC of 0.78, with a sensitivity of 67% (2/3), a specificity of 92% (54/59), and an overall accuracy of 90% (56/62). At the optimal cut-off value of 0.1, the corresponding Youden index was 0.58. These findings should be interpreted cautiously because only three bleeding events occurred in the validation set, resulting in substantial uncertainty in the estimated model performance. External validation in larger cohorts is required before the model can be generalized to other populations (Fig. 2B, Table 6).

Calibration and Bootstrap Internal Validation of the Predictive Model

The final four-predictor model (M4) was further evaluated in the full cohort of 306 patients, including 24 postoperative bleeding events, using 1000 bootstrap resampling iterations. All bootstrap resampling iterations were completed.

Table 1. Baseline characteristics of different datasets.

Variables	Total (N = 306)	Training set (N = 244)	Validation set (N = 62)	*p*-value
Age (years)	6.00 (4.00, 7.00)	6.00 (4.00, 8.00)	6.00 (5.00, 7.00)	0.474
Height (cm)	121.50 (112.00, 132.75)	121.50 (112.00, 134.00)	121.50 (114.50, 130.00)	0.366
Weight (kg)	23.00 (19.00, 31.38)	23.75 (19.00, 33.00)	23.00 (20.00, 29.00)	0.584
BMI (kg/m^2)	15.97 (14.58, 18.81)	16.03 (14.57, 18.79)	15.44 (14.63, 18.81)	0.679
Disease duration (months)	12.00 (6.00, 24.00)	12.00 (6.00, 24.00)	12.00 (6.00, 24.00)	0.416
Surgery time (min)	22.00 (19.00, 26.00)	22.00 (19.00, 27.00)	20.00 (17.00, 24.00)	0.017
Postoperative hospital stay (d)	3.00 (3.00, 3.00)	3.00 (3.00, 3.00)	3.00 (3.00, 3.00)	0.174
WBC (×10^9/L)	7.70 (6.67, 9.31)	7.93 (6.78, 9.33)	7.40 (6.50, 8.29)	0.051
Neutrophil (×10^9/L)	3.37 (2.62, 4.41)	3.48 (2.63, 4.50)	3.29 (2.62, 4.04)	0.177
Lymphocyte (×10^9/L)	3.49 (2.87, 4.18)	3.56 (2.86, 4.28)	3.34 (2.88, 4.01)	0.360
Monocyte (×10^9/L)	0.51 (0.40, 0.63)	0.52 (0.42, 0.64)	0.45 (0.37, 0.54)	0.002
Platelet (×10^9/L)	333.50 (287.50, 378.00)	331.00 (286.75, 377.25)	345.00 (293.75, 382.50)	0.686
NLR	0.97 (0.71, 1.33)	0.96 (0.71, 1.32)	1.04 (0.65, 1.35)	0.803
PLR	94.23 (75.17, 116.41)	93.03 (76.11, 116.00)	99.22 (74.80, 117.46)	0.488
SII	322.97 (218.90, 464.88)	322.86 (220.07, 461.07)	330.99 (207.88, 506.06)	0.806
LMR	6.97 (5.50, 8.89)	6.96 (5.34, 8.53)	7.25 (5.82, 9.55)	0.078
NPR	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)	0.249
Sex [n (%)]				0.531
Female	99 (32.35)	81 (33.20)	18 (29.03)	
Male	207 (67.65)	163 (66.80)	44 (70.97)	
Asthma history [n (%)]	2 (0.65)	2 (0.82)	0 (0.00)	1.000
Tonsil infiltration degree [n (%)]				0.556
Mild	86 (28.10)	72 (29.51)	14 (22.58)	
Moderate	214 (69.93)	167 (68.44)	47 (75.81)	
Severe	6 (1.96)	5 (2.05)	1 (1.61)	
Coexisting sinusitis [n (%)]	5 (1.63)	5 (2.05)	0 (0.00)	0.587
Postoperative infection [n (%)]	16 (5.23)	14 (5.74)	2 (3.23)	0.541
Dietary compliance [n (%)]				0.789
Poor	21 (6.86)	18 (7.38)	3 (4.84)	
Moderate	35 (11.44)	27 (11.07)	8 (12.90)	
Good	250 (81.70)	199 (81.56)	51 (82.26)	
Effectiveness of postoperative education [n (%)]				0.695
Poor	25 (8.17)	21 (8.61)	4 (6.45)	
Moderate	36 (11.76)	27 (11.07)	9 (14.52)	
Good	245 (80.07)	196 (80.33)	49 (79.03)	
Postoperative pain [n (%)]	201 (65.69)	168 (68.85)	33 (53.23)	0.021

Note: BMI, body mass index; WBC, white blood cell count; NLR, neutrophil-to-lymphocyte ratio; PLR, platelet-to-lymphocyte ratio; SII, systemic immune-inflammation index; NPR, neutrophil-to-platelet ratio; LMR, lymphocyte-to-monocyte ratio.

The apparent AUC was 0.955, the optimism-corrected AUC was 0.945, and the bootstrap out-of-bag AUC was 0.935 (95% CI: 0.875–0.995). Calibration performance was adequately evaluated using 1000 bootstrap resampling iterations. The model yielded a Brier score of 0.035, a calibration intercept of 0.045, and a calibration slope of 1.418, indicating potential limitations in calibration. The calibration curve showed reasonable agreement at lower predicted probabilities, although some underestimation of bleeding risk was observed in higher-risk patients (Fig. 3). The optimal probability cutoff was 0.114, corresponding to a Youden index of 0.811, sensitivity of 0.875, and specificity of 0.936. Given the limited number of bleeding events, this cutoff should be considered exploratory.

Discussion

In this retrospective cohort study, LASSO logistic regression with cross-validation retained four predictors of postoperative bleeding: postoperative infection, dietary compliance, age, and postoperative pain. The final model showed high apparent discrimination, with an AUC of 0.955. After 1000 bootstrap resampling iterations, the optimism-corrected AUC was 0.945, and the bootstrap out-of-bag AUC was 0.935 (95% CI: 0.875–0.995). The bootstrap out-of-bag calibration intercept, calibration slope, and Brier score were 0.045, 1.418, and 0.035, respectively. These findings suggest that the model may assist in postoperative bleeding risk assessment; however, its performance requires cautious interpretation and external validation.

Table 2. Baseline characteristics of children in the bleeding and non-bleeding groups in the training set.

Variables	Non-bleeding group (N = 223)	Bleeding group (N = 21)	*p*-value
Age (years)	6.00 (4.00, 7.00)	10.00 (7.00, 11.00)	<0.001
Height (cm)	120.00 (112.00, 132.00)	142.00 (123.00, 158.00)	<0.001
Weight (kg)	23.00 (19.00, 30.00)	42.00 (23.50, 55.00)	<0.001
BMI (kg/m^2)	15.97 (14.48, 18.37)	20.15 (15.38, 23.44)	0.002
Disease duration (months)	12.00 (6.00, 24.00)	24.00 (12.00, 36.00)	0.011
Surgery time (min)	22.00 (19.00, 26.00)	24.00 (21.00, 30.00)	0.093
Postoperative hospital stay (d)	3.00 (3.00, 3.00)	3.00 (3.00, 3.00)	0.120
WBC (×10^9/L)	7.93 (6.73, 9.36)	7.81 (6.88, 8.87)	0.850
Neutrophil (×10^9/L)	3.43 (2.58, 4.51)	3.64 (3.14, 4.48)	0.370
Lymphocyte (×10^9/L)	3.64 (2.93, 4.29)	3.07 (2.61, 3.72)	0.037
Monocyte (×10^9/L)	0.53 (0.42, 0.66)	0.44 (0.38, 0.57)	0.052
Platelet (×10^9/L)	335.00 (286.00, 378.00)	306.00 (293.00, 337.00)	0.150
NLR	0.93 (0.71, 1.31)	1.19 (1.04, 1.44)	0.036
PLR	92.09 (74.93, 114.02)	108.92 (93.02, 117.24)	0.150
SII	305.97 (219.62, 460.88)	369.49 (288.08, 515.08)	0.210
LMR	6.96 (5.36, 8.53)	6.95 (5.13, 8.17)	0.870
NPR	0.01 (0.01, 0.01)	0.01 (0.01, 0.02)	0.042
Sex [n (%)]			0.325
Female	72 (32.29)	9 (42.86)	
Male	151 (67.71)	12 (57.14)	
Asthma history [n (%)]	1 (0.45)	1 (4.76)	0.165
Tonsil infiltration degree [n (%)]			0.098
Mild	66 (29.60)	6 (28.57)	
Moderate	154 (69.06)	13 (61.90)	
Severe	3 (1.35)	2 (9.52)	
Coexisting sinusitis [n (%)]	4 (1.79)	1 (4.76)	0.365
Postoperative infection [n (%)]	3 (1.35)	11 (52.38)	<0.001
Dietary compliance [n (%)]			0.029
Poor	14 (6.28)	4 (19.05)	
Moderate	23 (10.31)	4 (19.05)	
Good	186 (83.41)	13 (61.90)	
Effectiveness of postoperative education [n (%)]			0.094
Poor	19 (8.52)	2 (9.52)	
Moderate	22 (9.87)	5 (23.81)	
Good	182 (81.61)	14 (66.67)	
Postoperative pain [n (%)]	147 (65.92)	21 (100.00)	0.001

No statistically significant differences ($p > 0.05$) were found between the two groups for sex, history of asthma, tonsil infiltration degree, comorbid sinusitis, operative time, length of postoperative hospitalization, white blood cell count, neutrophil count, monocyte count, platelet count, PLR, SII and LMR.

Although the model demonstrated high discrimination, the AUC estimates should be interpreted cautiously. Only 24 bleeding events occurred in the full cohort, making the apparent performance susceptible to sampling variability and optimism. The relatively homogeneous case mix and clinical practices of this single center may also have contributed to the high AUC. In addition, the retrospective ascertainment and strong separation of some postoperative predictors between the outcome groups may have inflated the model's discrimination. The calibration slope of 1.418 further indicated that the predicted probabilities were overly compressed, with some underestimation of bleeding risk among higher-risk patients. Therefore, the current findings represent preliminary internal validation rather than evidence of excellent performance or broad generalizability.

Several prediction models for post-tonsillectomy hemorrhage have previously been reported. Hu et al. [8] developed five machine learning models using data from 520 patients, including 60 hemorrhage events. Their best-performing XGBoost model incorporated demographic, clinical, laboratory, and surgical variables, including age, BMI, season, blood type, INR, adenoidectomy, surgical wound characteristics, and glucocorticoid use, and

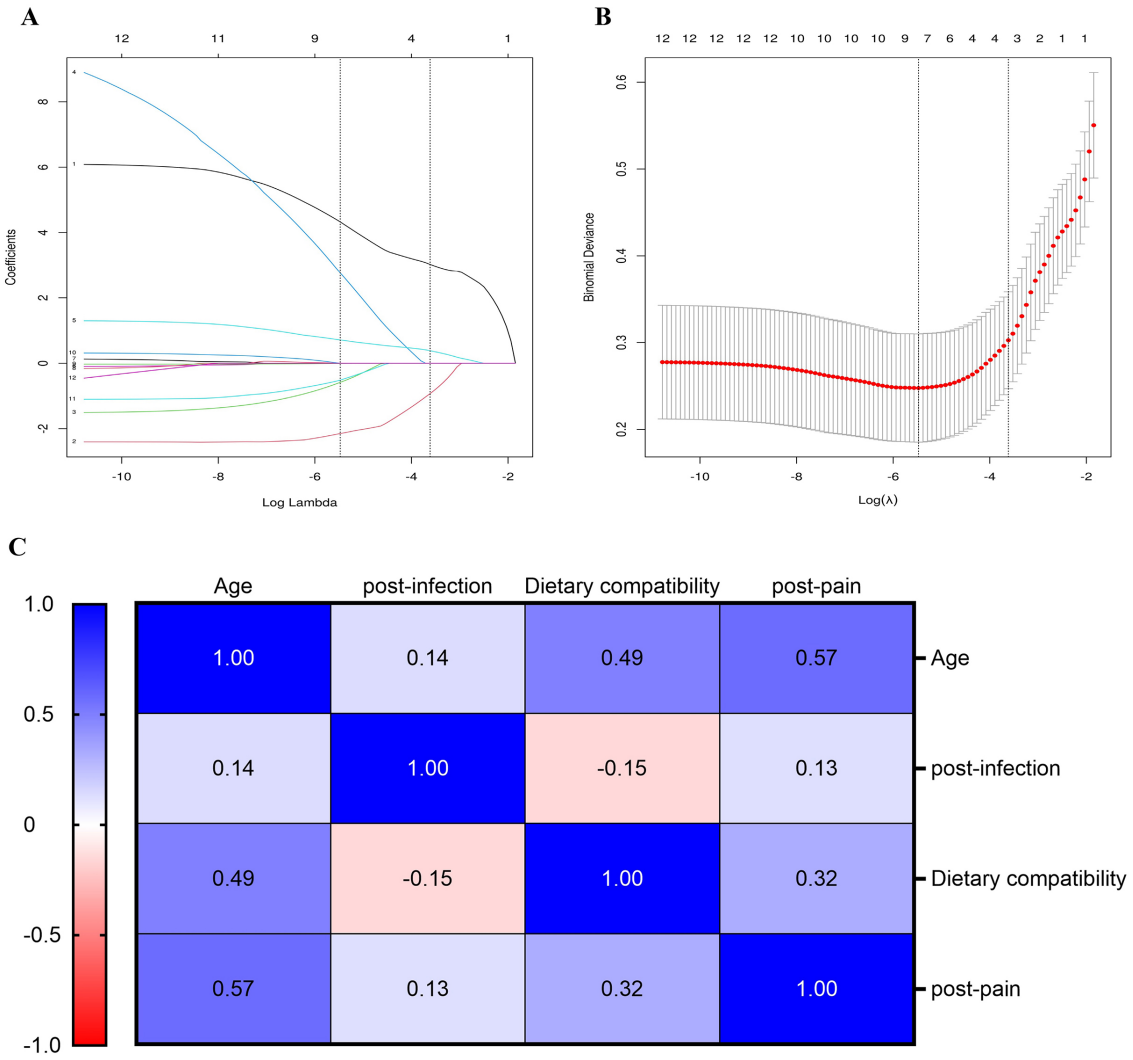


Fig. 1. Variable selection results. (A) Least absolute shrinkage and selection operator (LASSO) coefficient profiles for the 12 candidate predictors. The x-axis represents log(λ), and the y-axis represents the regression coefficients. Variables 1–12 denote postoperative infection, dietary compliance, effectiveness of postoperative education, postoperative pain, age, height, weight, body mass index (BMI), disease duration, lymphocyte count, neutrophil-to-lymphocyte ratio (NLR), and neutrophil-to-platelet ratio (NPR), respectively. (B) Ten-fold cross-validation curve. The x-axis represents log(λ), and the y-axis represents the cross-validated binomial deviance. Red points indicate the mean deviance, and gray error bars represent ±1 standard error. The left and right vertical dotted lines indicate lambda.min and lambda.1se, respectively. lambda.min minimizes the cross-validated binomial deviance, whereas lambda.1se is the largest λ within one standard error of the minimum. The numbers above panels A and B indicate the number of non-zero coefficients. (C) Spearman correlation matrix for the four predictors retained at lambda.1se. The color scale represents Spearman's correlation coefficient (ρ), ranging from −1 to 1.

achieved an AUC of 0.812. Ge et al. [9] subsequently evaluated logistic regression and seven machine learning algorithms in 492 pediatric patients. Their XGBoost model achieved a validation AUC of approximately 0.78, with important predictors including age, perioperative corticosteroid and NSAID use, surgical procedure, concurrent adenoidectomy, APTT, and fibrinogen. More recently, Xu et al. [10] developed a weighted logistic nomogram in 15,729 children undergoing Coblation tonsillectomy. Severe tonsillar embedding, junior surgeon status, obesity, poor postoperative diet, and age ≥12 years were retained as predictors; the model achieved an AUC of 0.816 and a Brier score of 0.0155 after 1000 bootstrap resamples [8,9,10].

The present model differs from these previous models by combining age with postoperative infection, dietary compliance, and postoperative pain. The association of older age and poor postoperative diet with bleeding is consistent with the findings of Xu et al. [10], whereas postoperative infection and pain were not included in their nomogram. Conversely, our model did not incorporate tonsillar embedding, surgeon experience, obesity, surgical technique, medication exposure, or coagulation measurements, which

Table 3. LASSO regression coefficients.

Factors	Coefficient at lambda.min (minimum cross-validated binomial deviance; λ = 0.005)	Coefficient at lambda.1se (one-standard-error rule; λ = 0.022)
Postoperative infection	4.69	3.36
Dietary compliance	–1.94	–0.88
Effectiveness of postoperative education	–0.34	0.00
Postoperative pain	2.20	1.70
Age	0.76	0.46
Height	0.00	0.00
Weight	0.00	0.00
BMI	0.02	0.00
Disease duration	–0.01	0.00
Lymphocytes	0.00	0.00
NLR	–0.66	0.00
NPR	0.00	0.00

LASSO, least absolute shrinkage and selection operator.

Table 4. Spearman correlation analysis among predictive variables.

Variables	Age		Postoperative infection		Dietary compliance		Postoperative pain	
	r	*p*	*r*	*p*	*r*	*p*	*r*	*p*
Age	1.00	<0.001	0.14	0.03	0.49	<0.001	0.57	<0.001
Postoperative infection	0.14	0.03	1.00	<0.001	–0.15	0.02	0.13	0.05
Dietary compliance	0.49	<0.001	–0.15	0.02	1.00	<0.001	0.32	<0.001
Postoperative pain	0.57	<0.001	0.13	0.05	0.32	<0.001	1.00	<0.001

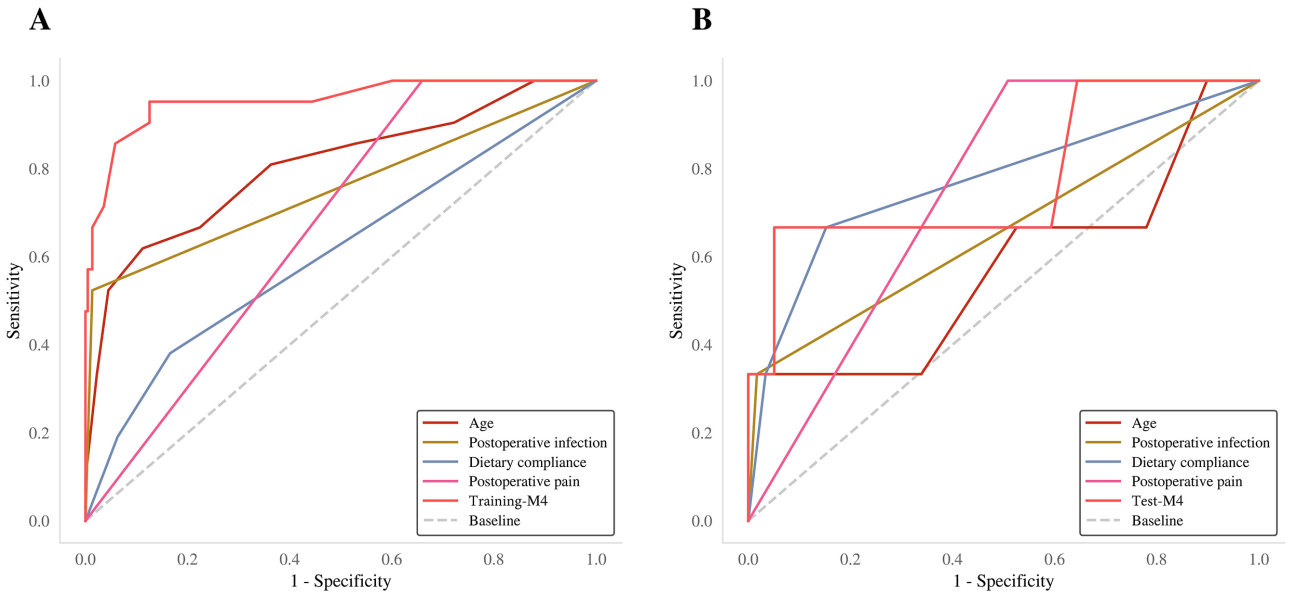


Fig. 2. Receiver operating characteristic (ROC) curve analysis of the predictive model performance. (A) ROC curves in the training set (n = 244; 21 bleeding and 223 non-bleeding cases). (B) ROC curves in the validation set (n = 62; 3 bleeding and 59 non-bleeding cases). M4 comprises age, postoperative infection, dietary compliance, and postoperative pain. The x-axis represents 1 − specificity (false-positive rate), and the y-axis represents sensitivity (true-positive rate). The diagonal dashed line represents discrimination expected by chance (area under the curve (AUC) = 0.50).

were important predictors in previous studies. The use of only four routinely recorded variables makes the model relatively simple and interpretable. In addition, the study focused specifically on children undergoing adenotonsillectomy using low-temperature plasma radiofrequency ablation and included bootstrap out-of-bag assessment of discrimination and calibration. However, the higher AUC observed in our study should not be interpreted as evidence

Table 5. Predictive performance of the LASSO cross-validation model in the training set.

Variables	AUC	Sensitivity	Specificity	Youden index	Optimal cut-off	Accuracy
Age	0.81	0.62	0.89	0.51	9.00	0.87
Postoperative infection	0.76	0.52	0.99	0.51	1.00	0.95
Dietary compliance	0.61	0.38	0.83	0.22	3.00	0.80
Postoperative pain	0.67	1.00	0.34	0.34	1.00	0.40
Model M4 (Training Set)	0.96	0.95	0.87	0.83	0.09	0.88

Note: AUC, area under the curve.

Table 6. Predictive performance of the LASSO cross-validation model in the validation set.

Variables	AUC	Sensitivity	Specificity	Youden index	Optimal cut-off	Accuracy
Age	0.58	0.33	0.93	0.27	9.0	0.90
Postoperative infection	0.66	0.33	0.98	0.32	1.0	0.95
Dietary compliance	0.77	0.67	0.85	0.51	3.0	0.84
Postoperative pain	0.75	1.00	0.49	0.49	1.0	0.52
Model M4 (Validation Set)	0.78	0.67	0.92	0.58	0.1	0.90

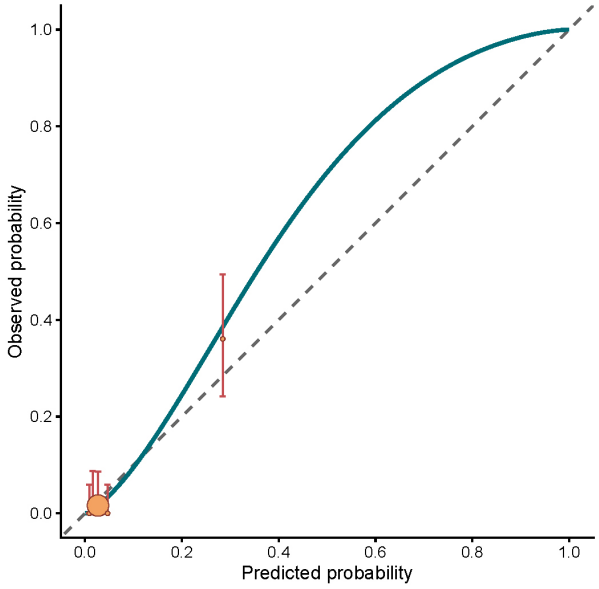


Fig. 3. Bootstrap out-of-bag calibration curve of the four-predictor model (M4). The solid line represents the bootstrap out-of-bag calibration curve, whereas the dashed 45-degree line represents perfect calibration. The circles indicate the observed postoperative bleeding incidence across five predicted-risk groups, with error bars representing 95% confidence intervals. Predictions were aggregated across 1000 bootstrap resampling iterations.

that the model is superior, because it was derived from only 306 patients and 24 bleeding events at a single center. Furthermore, postoperative infection, dietary compliance, and pain may be suitable for postoperative risk reassessment only when they are recorded before bleeding onset; otherwise, their inclusion may introduce temporal information leakage. Therefore, prospective multicenter external validation using standardized assessment time points is required.

In the present study, older age was associated with an increased risk of postoperative bleeding. This is consistent with prior studies [11,12], emphasizing the importance of meticulous postoperative management in older pediatric populations. The increased bleeding risk in older children may be related to broader surgical wound beds with thicker eschars and greater mechanical stress exerted by stronger pharyngeal musculature. Notably, Alsalamah et al. [13] identified age ≥12 years as a significant predictor of post-tonsillectomy bleeding (OR: 2.685, $p = 0.027$). In contrast, the optimal cutoff value for age was 9 years in the ROC analysis, which may be attributed to differences in surgical approach—specifically, the use of low-temperature plasma techniques—and potential ethnic or demographic variations.

In our study, postoperative pain and poor dietary compliance emerged as two additional significant risk factors for postoperative bleeding. The association between severe postoperative pain and bleeding has been extensively documented. Pediatric patients typically experience peak pain intensity between the fourth and fifth postoperative days, a period during which the risks of bleeding, dehydration, and feeding difficulties are markedly elevated—factors that significantly impede recovery [3,14,15,16]. These findings underscore the critical role of effective postoperative analgesia, with multimodal pain management strategies shown to substantially reduce rates of readmission and reoperation due to bleeding [12,17].

Poor dietary compliance—such as premature feeding or consumption of overly hot or irritant foods—can directly traumatize the surgical site and lead to vascular rupture. Additionally, insufficient nutritional intake may delay tissue healing and compromise vascular stability, thereby elevating the risk of postoperative bleeding. Prior research has also indicated that, despite advances in tonsillectomy techniques, challenges with postoperative oral intake persist and remain a major contributor to delayed recovery and

increased hospital readmission [18,19]. Consequently, addressing nutritional intake and improving feeding practices in the postoperative period are essential to minimizing hemorrhagic complications and enhancing recovery outcomes in pediatric patients.

Notably, postoperative infection also emerged as a significant risk factor—an association rarely explored in the context of tonsillectomy and adenoidectomy. Infections can exacerbate pain [20] and release inflammatory cytokines such as IL-6 and TNF-α, which disrupt wound healing and increase the likelihood of secondary bleeding and reoperation [21]. These findings highlight the importance of effective postoperative infection control strategies.

Overall, the findings of this study offer important practical implications for predicting postoperative bleeding risk in children undergoing adenotonsillectomy using low-temperature plasma radiofrequency ablation. To our knowledge, this is the first study to apply a machine learning algorithm to develop a predictive model tailored to this patient population. The model we constructed is notably simple, incorporating only four readily accessible clinical variables, which enhances its potential for adoption across various healthcare settings. However, as a single-center retrospective study, this work has several limitations. Furthermore, the model has undergone internal validation only, and future research should focus on external validation to further assess its generalizability.

Several limitations should be acknowledged. First, this was a retrospective, single-center cohort study without matching, and residual selection bias, confounding, and record-related measurement bias may remain. Second, only 24 postoperative bleeding events were observed, and out-of-hospital events relied on documented follow-up contacts and re-presentation to medical attention; therefore, the possibility of incomplete outcome ascertainment cannot be entirely excluded. Although LASSO regularization and bootstrap validation were applied, the limited event count may still have resulted in overfitting and optimistic performance estimates; therefore, the reported cutoff should be considered exploratory. Third, postoperative bleeding was analyzed only as a binary outcome because its frequency, location, severity, and primary/secondary classification were not consistently documented, which may have introduced outcome misclassification. Fourth, because this was a retrospective study, the evaluation of some indicators may not be sufficiently accurate. For example, pain was extracted as a binary variable from routine nursing records rather than measured with a standardized pain scale, which may introduce variability in assessment. For postoperative infection, the diagnosis was based on routine clinical documentation rather than a prespecified standardized criterion, which may also lead to certain limitations in the results. Furthermore, the inclusion of postoperative variables introduces inherent temporal ambiguity. Because the exact temporal relationship between predictors such as pain or infection and hemorrhagic events could not be definitively confirmed, we revised the conceptual framework of this study. Due to the retrospective nature of data collection, the temporal sequence between bleeding onset and assessments of postoperative infection, pain, and dietary compliance could not be established with certainty. Consequently, this model cannot be interpreted as an early prediction model. It should be strictly utilized as a concurrent postoperative risk-assessment tool designed to identify high-risk profiles during recovery. Future prospective studies with standardized, time-stamped assessments are required to establish strict temporal causality. Finally, center-specific surgical techniques, operator experience, and postoperative management protocols may limit generalizability. Larger prospective multicenter studies with standardized pre-event assessments, detailed bleeding classifications, and external validation are required.

Conclusions

This study identified postoperative infection, poor dietary compliance, postoperative pain, and age as predictors retained by the LASSO model for postoperative bleeding in pediatric patients undergoing adenotonsillectomy using low-temperature plasma radiofrequency ablation. The predictive model developed using the LASSO cross-validation algorithm demonstrates strong potential as an effective tool for the postoperative risk assessment of children at elevated risk of postoperative bleeding.

Availability of Data and Materials

The data analyzed are available from the corresponding author upon reasonable request.

Author Contributions

QC and LL conceived and designed the study. YY contributed substantially to the collection and statistical analysis of clinical data from pediatric patients and drafted the manuscript. LL performed a comprehensive review of prediction models. QC provided principal guidance in the development of the study design. All authors have been involved in revising the manuscript critically for important intellectual content. All authors gave final approval of the version to be published. All authors have participated sufficiently in the work to take public responsibility for appropriate portions of the content and agreed to be accountable for all aspects of the work in ensuring that questions related to its accuracy or integrity.

Ethics Approval and Consent to Participate

This study was conducted in accordance with the principles of the Declaration of Helsinki and received approval from the Ethics Committee of Anhui Children's Hospital (Approval Number: EYLL-2026-038). No patient-identifiable information was disclosed beyond the scope of the data

analyses performed in this study. Because this was a retrospective study using de-identified clinical data, the requirement for written informed consent was waived by the Ethics Committee of Anhui Children's Hospital.

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Conflict of Interest

The authors declare no conflict of interest.

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