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Original Article

Predictive value of erythrocyte sedimentation rate, albumin and CRP for infection risk in elderly rheumatoid arthritis patients undergoing treatment

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Abstract: Objective: To develop a predictive model for infection risk in elderly rheumatoid arthritis (RA) patients using laboratory markers, particularly erythrocyte sedimentation rate (ESR), albumin (ALB), and C-reactive protein (CRP). Methods: This retrospective study included 452 elderly RA patients admitted to the Hospital of Chengdu University of Traditional Chinese Medicine between January 2021 and June 2024. The patients were randomly divided into a training group (271 patients) and a validation group (181 patients) at a 6:4 ratio. Key clinical and laboratory data were collected, including ESR, ALB, CRP, and others. Lasso regression and multivariable logistic regression were employed to identify infection-related factors. Model performance was evaluated using receiver operating characteristic (ROC) curves, calibration curves, and decision curve analysis (DCA). Results: The study identified ALB<33.75 g/L, CRP≥32.75 mg/L, and ESR≥51.50 mm/h as independent risk factors for infection in elderly RA patients. A predictive model incorporating these three markers demonstrated high diagnostic accuracy, with an AUC of 0.909 in the training group and 0.880 in the validation group. DCA further confirmed the clinical utility of the model. Conclusions: This study successfully developed a predictive model combining ESR, ALB, and CRP to assess infection risk in elderly RA patients. This model has significant potential to enhance early infection detection and support clinical decision-making, offering a valuable tool for managing this vulnerable population.

Keywords: Elderly rheumatoid arthritis, erythrocyte sedimentation rate, albumin, infection risk, lasso regression

Introduction

Rheumatoid arthritis (RA) is a chronic autoimmune disorder characterized by persistent joint inflammation, swelling, and pain [1]. Its pathogenesis is closely associated with immune system dysfunction, particularly involving abnormal T cells, B cells, and immunoglobulin responses [2]. RA causes joint deformities, functional disabilities, and, in the long term, permanent disability, imposing substantial physical and psychological burdens on patients and lowering their quality of life [2]. The primary treatment for RA involves disease-modifying antirheumatic drugs (DMARDs), particularly immunosuppressants and biologic agents [3]. While these therapies effectively alleviate symptoms and control inflammation, they suppress normal immune functions, increasing the risk of infections. Infections are a common complication during RA treatment, especially in elderly patients who often experience diminished immune function, comorbidities, and prolonged use of immunosuppressive drugs, all of which elevate their infection risk [4]. Infections not only complicate treatment but can also lead to delayed therapy, hospitalization, and even death [5]. Consequently, predicting and managing infection risk in RA patients is a critical challenge in clinical practice.

Erythrocyte sedimentation rate (ESR) and albumin (ALB) are commonly used clinical laboratory markers with significant diagnostic value in RA and other inflammatory diseases [6, 7]. Increased ESR reflects elevated levels of acute-phase reactants in the blood, indicating inflammation or injury [8]. In RA, ESR is routinely used to assess disease activity and monitor treatment response. Increased ESR has been shown

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to be closely associated with the pathological activity of RA and the risk of infection, particularly in patients undergoing immunosuppressive therapy [9]. As such, ESR serves as an early warning indicator of heightened infection risk.

ALB, the most abundant protein in plasma, plays a critical role in maintaining colloid osmotic pressure and transporting various bioactive substances [10]. A decrease in ALB levels often indicates malnutrition, chronic disease, or immune dysfunction. Research has demonstrated that lower ALB levels in RA patients are strongly linked to an increased risk of infection, as hypoalbuminemia not only reflects immune deficiency but is also directly associated with chronic inflammation and disease exacerbation [11]. Therefore, the combined monitoring of ESR and ALB levels holds substantial clinical value in predicting infection risk of RA patients.

Although some studies have explored the relationship between ESR and ALB levels and infection risk in RA patients, systematic analyses focusing on elderly patients remain limited. The novelty of this study lies in (1) developing a more precise infection prediction model using methodologies such as Lasso regression, ROC curves, and Akaike Information Criterion (AIC) model selection; (2) validating the model with large-scale clinical data to enhance its accuracy and reliability; and (3) evaluating the impact of different variable combinations on infection risk prediction, offering a more practical tool for clinicians. This study validates the effectiveness of ESR and ALB as infection predictors in elderly RA patients, providing evidence-based screening criteria for clinical practice.

Methods and materials

Sample size calculation

The sample size for this study was calculated using the standard formula: $N = Z^2 \times [P \times (1 - P)]/E^2$, where N is the required sample size, Z is the critical value under the standard normal distribution (typically 1.96 for a 95% confidence level), P is the expected event incidence, and E is the margin of error. Based on previous reports of adverse reactions related to JAK inhibitors (P = 0.287, and E = 0.05) [12], the required sample size was 314.22, which was rounded to 314 for analysis. The final sample size was determined based on clinical data collection.

Ethical declaration

The Medical Ethics Committee of the Hospital of Chengdu University of Traditional Chinese Medicine approved this study.

General information

The study retrospectively analyzed the data from 452 elderly RA patients admitted to the Hospital of Chengdu University of Traditional Chinese Medicine between January 2021 and June 2024.

Inclusion and exclusion criteria

Inclusion criteria: (1) Patients meeting the RA diagnostic criteria [13]; (2) Patients in the active phase of RA; (3) Age ≥60 years; (4) Complete clinical data available.

Exclusion criteria: (1) Patients with other autoimmune diseases, including Sjögren's syndrome, systemic lupus erythematosus, ankylosing spondylitis, systemic vasculitis, scleroderma, idiopathic inflammatory myopathy, Hashimoto's thyroiditis, or gouty arthritis; (2) Patients with malignant tumors; (3) Patients with severe organ dysfunction; (4) Patients infected with HIV or other serious bacterial infections; (5) Patients with cardiovascular or cerebrovascular diseases; (6) Female patients in pregnancy or lactation.

Infection definition

Infections were defined based on symptoms and laboratory indicators observed within six months after treatment. Infection sites included the lungs, urinary system, and upper respiratory tract. Symptoms such as frequent urination, urgency, dysuria, cough, and fever were monitored. If infection symptoms were present, venous blood was collected for routine blood tests, urine analysis, urine culture, and bacterial culture. A diagnosis of infection was confirmed if abnormalities were detected in white blood cell count, neutrophils, or lymphocytes, or if bacterial cultures yielded positive pathogens.

Grouping

The study included 452 patients, of whom 122 had infections. All patients were randomly

divided into a training group and a validation group in a 6:4 ratio. The training group consisted of 271 patients, including 77 with infections and 194 without, and the validation group included 181 patients, including 45 with infection and 136 without. The training group was used to construct and train the model, while the validation group was used to assess the model's generalizability and accuracy.

Clinical and laboratory data collection

Clinical data were obtained from electronic medical records and outpatient follow-up records, encompassing basic patient information and laboratory test results. Basic data included age (≥70 years and <70 years), gender (male, female), body mass index (BMI, ≥23 and <23), disease duration (≥5 years and <5 years), smoking history (yes, no), hypertension (yes, no), diabetes (yes, no), and disease activity score (DAS28, ≥3 and <3) [14]. Treatment information included non-steroidal anti-inflammatory drugs (NSAIDs) and corticosteroids (used, not used). Infection types were categorized as upper respiratory tract, urinary system, and other types.

Additionally, laboratory indicators such as albumin (ALB), C-reactive protein (CRP), immunoglobulins (IgG, IgA, IgM, IgE), rheumatoid factor (RF), creatinine (Cr), and erythrocyte sedimentation rate (ESR) were recorded. ALB, CRP, IgG, IgA, IgM, IgE, and RF were detected using the Cobas c 702 immunoturbidimetry method (Model: Cobas c 702). The Cr level was assessed using enzymatic method with an automatic biochemical analyzer (Model: Hitachi 7600). ESR was detected directly using the automatic rapid blood sedimentation analyzer TEST-1.

Observation indicators

Primary observation indicators: The primary outcome of this study was to develop a predictive model for infection risk in elderly RA patients by integrating clinical and laboratory indicators, including ESR, ALB, and CRP. The receiver operating characteristic (ROC) curve was used to assess the model's ability to distinguish between infected and non-infected cases, with the area under the curve (AUC) serving as a measure of diagnostic accuracy. A calibration curve was employed to compare predicted infection probabilities with actual infection rates, evaluating the alignment between predicted and observed results. Decision Curve Analysis (DCA) was used to assess the clinical utility of the model by analyzing net benefit at different probability thresholds, thereby aiding clinical decision-making.

Secondary observation indicators: Baseline data were compared between infected and non-infected patients in the training and validation groups. Lasso regression was used to identify characteristics significantly associated with infection risk from multiple clinical and laboratory variables. Each infection-related characteristic (e.g., ESR, ALB, CRP) was evaluated through ROC curve analysis. The predictive accuracy of single and multi-variable models was assessed, and AUC values were compared for various combinations (e.g., ALB + CRP + ESR and ALB + ESR) to determine the most effective prediction model.

Statistical analysis

Data analysis was conducted using SPSS 26.0 and R 4.3.3 statistical software. Normality of data was assessed using the Kolmogorov-Smirnov (K-S) test. For continuous variables with normal distribution, independent sample t-tests were used for intergroup comparisons. For non-normally distributed variables, the rank sum test was applied. Chi-square tests were used for categorical variables. A backward logistic regression model was employed for multivariate analysis to identify factors affecting infection risk. ROC curves were used to evaluate the accuracy of different variables in predicting infection risk, with the best model selected based on AIC analysis. The Delong test was used to compare the AUC of different models. Calibration curves were plotted to assess model fit, and the Hosmer-Lemeshow test was performed. Additionally, DCA was used to evaluate the clinical utility of each feature. All statistical tests were two-sided, and a P value <0.05 was considered statistically significant.

Results

Baseline comparison of infection occurrence in the training and validation groups

Baseline data were compared between patients with and without infections in both the training and validation groups. The proportion

of patients aged ≥70 years who developed infections was significantly higher than those aged <70 in both the training (P = 0.013) and the validation group (P = 0.002). Diabetes (P<0.001 in the training group, P = 0.027 in the validation group) and a DAS28 ≥3 (P = 0.022 in the training group, P = 0.002 in the validation group) were strongly associated with infection in both groups. Additionally, corticosteroid use was significantly associated with infection in both the training group (P = 0.013) and the validation group (P = 0.025) (**Table 1**).

Lasso regression of seven variables in the training group

Lasso regression was applied to analyze seven different variables in the training group. The Lasso coefficient selection process revealed that the model coefficients gradually approached zero as log(λ) increased, eventually stabilizing. The minimum point (λ = 0.0041396) included all seven variables, whereas the λ = 0.038606 (corresponding to the. 1se point) included only five variables: ALB, CRP, ESR, age, and DAS28 (**Figure 1A**). To ensure model generalizability, we selected the five variables included at λ = 1se. The trajectories of these variables at different λ values further supported this decision (**Figure 1B**).

ROC curve analysis of the five variables in the training and validation groups

In the training group, the AUCs for ALB, CRP, ESR, age, and DAS28 were 0.810, 0.680, 0.794, 0.584, and 0.576, respectively (**Figure 2A**). Among these, ALB, CRP, and ESR demonstrated the highest diagnostic value for distinguishing between infection and non-infection groups. In the validation group, the AUCs for ALB, CRP, ESR, age, and DAS28 were 0.895, 0.768, 0.722, 0.635, and 0.631, respectively (**Figure 2B**). These variables all exhibited moderate to strong diagnostic capabilities.

Multivariate logistic regression for identifying independent risk factors for infection

Multivariate logistic regression was performed using five variables (**Table 2**). For continuous variables (ALB, CRP, ESR), cutoff values were used for classification, while categorical data (age, disease activity score, infection status) were trained according to their original categories. The results revealed that ALB, CRP, and ESR were independent risk factors significantly associated with infection. Specifically, the β-value for ALB was -2.123 (P<0.001), indicating that when ALB levels were below 33.75 g/L, the risk of infection significantly increased (OR = 0.12, 95% CI: 0.060-0.237). The β-value for CRP was 0.796 (P = 0.022), suggesting that when CRP levels were ≥32.75 mg/L, the risk of infection increased (OR = 2.216, 95% CI: 1.124-4.371). The β-value for ESR was 1.767 (P<0.001), showing that when ESR was ≥51.50 mm/h, the infection risk significantly increased (OR = 5.852, 95% CI: 2.909-11.775). Although age (P = 0.059) and disease activity score (P = 0.061) were close to being significant, their effects was weaker, with OR values of 1.94 (age) and 1.945 (disease activity score), indicating a less substantial impact on infection occurrence (**Tables 3**, **4**).

AIC value distribution and ROC curve comparison for models in the training group

We selected three risk factors through logistic regression and constructed different models. The ALB + CRP + ESR model demonstrated the lowest AIC value (191.57), suggesting a better model fit than other models (**Figure 3**). Subsequently, ROC curves for the ALB + CRP + ESR and ALB + ESR models were plotted in the training group (**Figure 4**). The AUC for the ALB + CRP + ESR model was 0.909, while the AUC for the ALB + ESR model was 0.891. The Delong test revealed no significant difference in AUC between the two models (0.052 difference). Nevertheless, due to the simplicity and cost-effectiveness of CRP testing, the ALB + CRP + ESR model was selected as the optimal model.

Comparison and evaluation of model performance in the training and validation groups

The accuracy, stability, and clinical utility of the model were evaluated using ROC, calibration, and DCA curves. The ROC curve (**Figure 5**) showed an AUC of 0.909 for the training group and 0.880 for the validation group, indicating better performance in the training group while maintaining high diagnostic accuracy in the validation group. The calibration curve (**Figure 6**) showed a C-index of 0.909 for the training group and 0.884 for the validation group, indicating good calibration ability. The Hosmer-Lemeshow test showed a *P*-value of 0.021 for

Table 1. Comparison of baseline data between infection and non-infection groups in both the training and validation groups

Variable	Training Group (n = 271)		*P*-value	Validation Group (n = 181)		*P*-value
	Infection Group (n = 77)	Non-Infection Group (n = 194)		Infection Group (n = 45)	Infection Group (n = 136)	
Age						
≥70 years	51	96	0.013	32	60	0.002
<70 years	26	98		13	76	
Gender						
Male	23	70	0.331	17	45	0.566
Female	54	124		28	91	
BMI						
≥23 kg/m^2	22	75	0.118	21	54	0.411
<23 kg/m^2	55	119		24	82	
Disease Duration						
≥5 years	56	119	0.077	34	90	0.240
<5 years	21	75		11	46	
Smoking History						
Yes	34	70	0.218	16	55	0.561
No	43	124		29	81	
Hypertension						
Yes	10	35	0.313	8	24	0.984
No	67	159		37	112	
Diabetes						
Yes	18	16	<0.001	10	13	0.027
No	59	178		35	123	
DAS28						
≥3 points	53	104	0.022	32	61	0.002
<3 points	24	90		13	75	
Nonsteroidal Anti-inflammatory Drugs (NSAIDs)						
Used	51	116	0.326	30	98	0.491
Not used	26	78		15	38	
Corticosteroids						
Used	37	62	0.013	24	47	0.025
Not used	40	132		21	89	
Infection Type						
Upper Respiratory Tract	54	141	0.915	29	90	0.444
Urinary System	16	37		10	36	
Other	7	16		6	10	
ALB (g/L)	31.55±4.32	36.56±3.74	<0.001	30.04±4.26	36.84±3.66	<0.001

CRP (mg/L)	34.00 [23.00, 52.90]	24.40 [14.72, 34.12]	<0.001	39.10 [28.70, 51.90]	23.40 [14.30, 32.15]	<0.001
IgG (IU/mL)	13.53±3.09	13.88±3.00	0.383	13.31±3.18	13.87±3.03	0.288
IgA (IU/mL)	3.10±0.76	3.13±0.81	0.757	3.01±0.73	3.06±0.89	0.762
IgM (IU/mL)	1.54 [1.18, 1.92]	1.52 [1.09, 1.94]	0.630	1.52 [1.10, 1.66]	1.60 [1.13, 2.09]	0.174
IgE (IU/mL)	114.98±44.25	115.46±48.00	0.940	119.73±48.57	115.24±50.26	0.602
RF (IU/ml)	157.31±13.20	159.16±15.15	0.347	156.37±17.14	157.94±16.18	0.578
Cr (μmol/L)	46.53±7.18	45.72±8.78	0.476	45.81±7.67	44.73±7.81	0.421
ESR (mm/h)	55.00 [52.00, 60.00]	48.00 [41.00, 54.00]	<0.001	53.33±7.80	46.38±9.08	<0.001

Note: BMI, body mass index; DAS28, Disease Activity Score 28; ALB, albumin; CRP, C-reactive protein; IgG, immunoglobulin G; IgA, immunoglobulin A; IgM, immunoglobulin M; IgE, immunoglobulin E; ESR, erythrocyte sedimentation rate; RF, rheumatoid factor; Cr, creatinine.

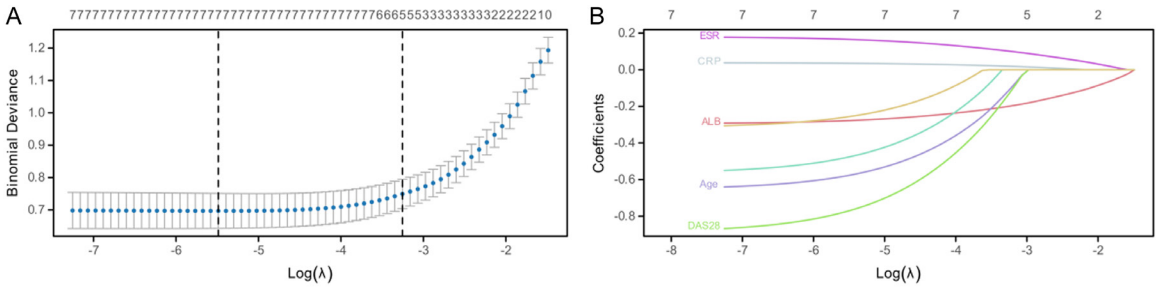

Figure 1. Lasso regression analysis of 7 variables in the training group. A: Diagnostic Lasso Coefficient Selection. B: Diagnostic Lasso Variable Trajectories. Note: Lasso, Lasso Regression; Log, Logarithmic Transformation; CRP, C-reactive protein; ALB, albumin; ESR, erythrocyte sedimentation rate; DAS28, Disease Activity Score 28.

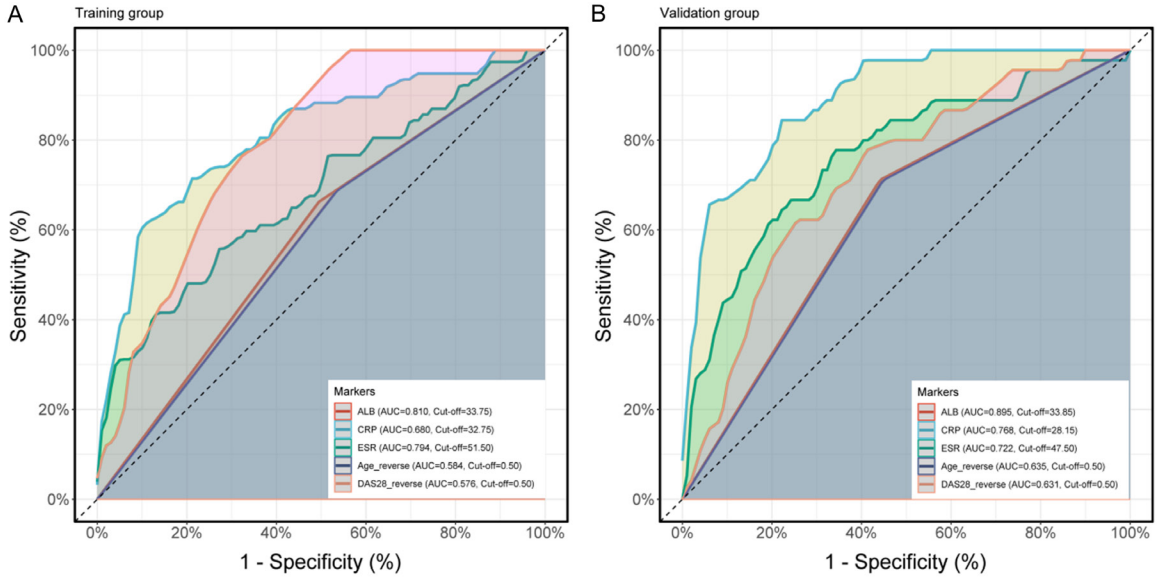

Figure 2. ROC curve analysis of 5 variables in the training and validation groups. A: ROC curve for 5 variables in the training group. B: ROC curve for 5 variables in the validation group. Note: ROC, receiver operating characteristic; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate; DAS28, Disease Activity Score 28.

Table 2. Variable assignment table

Variable	Variable Type	Assignment
ALB (g/L)	(Independent variable)	≥33.75 = 1, <33.75 = 0
CRP (mg/L)	(Independent variable)	≥32.75 = 1, <32.75 = 0
ESR (mm/h)	(Independent variable)	≥51.50 = 1, <51.50 = 0
Age (Years)	(Independent variable)	≥60 = 1, <60 = 0
DAS28	(Independent variable)	≥3 = 1, <3 = 0
Infection	(Dependent variable)	Yes = 1, No = 0

Note: ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate; DAS28, Disease Activity Score 28.

the training group and 0.04 for the validation group, demonstrating that the model fits reasonably in both groups. Finally, the DCA curve (**Figure 7**) showed that the model provided net benefits across the high-risk threshold range of 0-94% in the training group and 0-96% in the validation group, suggesting substantial clinical decision-making value.

Discussion

Erythrocyte sedimentation rate (ESR) and albumin (ALB) are common clinical laboratory markers widely used in diagnosing and predicting various diseases [15]. ESR reflects the inflammatory status in the body, while ALB levels are typically associated with nutritional status and immune function [16]. Recent studies have highlighted the value of these markers in early infection

Table 3. Multivariate logistic regression for identifying independent risk factors for infection

Variable	β	Standard Error	Wald	Significance	OR	95% CI	
						Lower	Upper
ALB	-2.123	0.348	37.234	<0.001	0.12	0.060	0.237
CRP	0.796	0.346	5.274	0.022	2.216	1.124	4.371
ESR	1.767	0.357	24.534	<0.001	5.852	2.909	11.775
Age	0.663	0.351	3.566	0.059	1.94	0.975	3.858
DAS28	0.666	0.355	3.507	0.061	1.945	0.969	3.904
Constant	-1.844	0.459	16.143	<0.001	0.158		

Note: ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate; DAS28, Disease Activity Score 28; OR, odds ratio; CI, confidence interval.

Table 4. ROC curve analysis for models in the training group

Marker	CI lower upper	Specificity	Sensitivity	Youden index	Cut off	Accuracy	Precision	F1 Score
ALB + CRP + ESR	0.875-0.943	74.23%	92.21%	66.43%	0.178	79.34%	92.21%	71.72%
ALB + ESR	0.852-0.930	78.35%	84.42%	62.77%	0.233	80.07%	84.42%	70.65%

Note: ROC, receiver operating characteristic; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

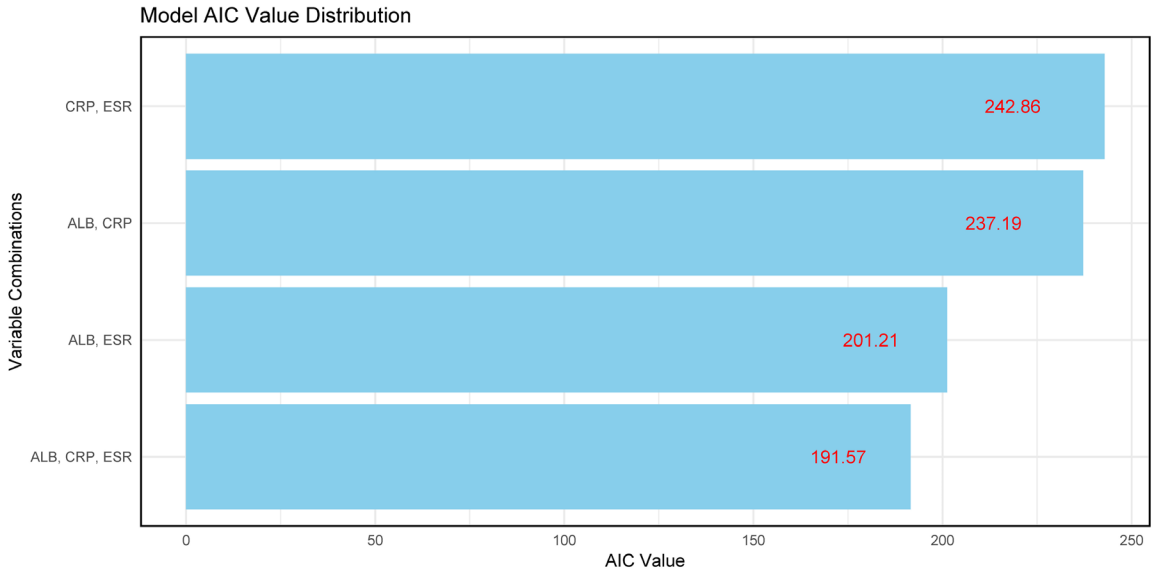

Figure 3. AIC value distribution in the training group. Note: AIC, Akaike information criterion; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

diagnosis. ESR is typically elevated in infectious diseases, which often trigger acute inflammatory responses, while ALB levels decrease in response to inflammation [17]. Therefore, investigating the roles of these two indicators in predicting infection holds significant clinical significance.

In this study, we explored the clinical relevance of ESR, ALB, and CRP in predicting infections. Analysis of clinical data from infected patients revealed a close association between these markers and infection occurrence, with their changes offering valuable diagnostic information. ESR is widely recognized as a non-specific marker of inflammation, and in our study, it was elevated during the acute phase of infection, with the degree of elevation correlating positively with infection severity. Specifically, ESR levels were significantly higher than expected, particularly in bacterial infections, and were often more sensitive than routine clinical symp-

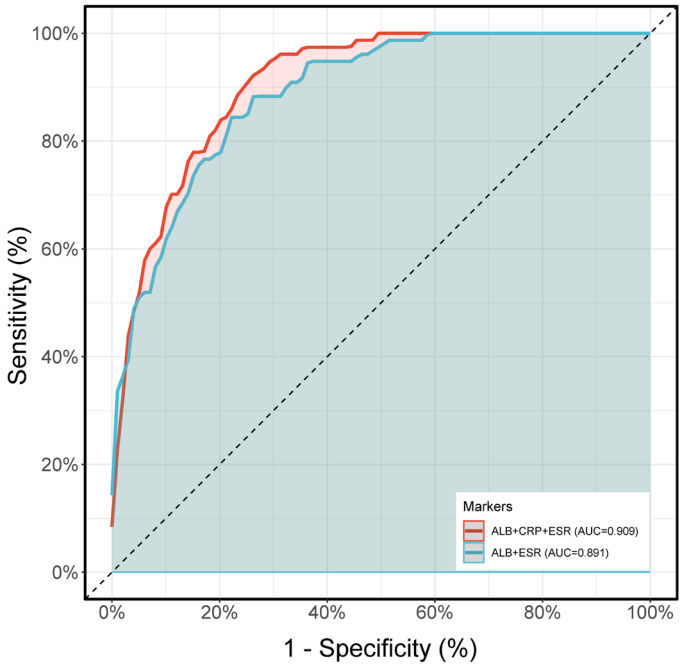

Figure 4. ROC curves for ALB + CRP + ESR model and ALB + ESR model in the training group. Note: ROC, receiver operating characteristic; AUC, area under curve; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

toms. For example, an elevated ESR was an early indicator of infection in patients with bacterial pneumonia and urinary tract infections. Thus, ESR can serve as a sensitive early detection marker for infections, especially bacterial infections, where its sensitivity is higher than other routine inflammatory markers, such as white blood cell count and body temperature. Similar findings have been reported, particularly for bacterial pneumonia, where increases in ESR and CRP are reliable early infection markers. For instance, a study by Leal et al. [18] indicated that ESR elevation in bacterial pneumonia patients was significantly more reliable than traditional markers like temperature and white blood cell count, suggesting ESR's higher sensitivity as an early infection marker. Furthermore, ESR has demonstrated higher specificity and sensitivity in predicting infections, particularly in diabetic patients, where it can reveal infection risks earlier [19]. These findings are consistent with our results.

ALB levels reflect not only nutritional status but also acute inflammatory responses in the body. In our study, infected patients exhibited significantly lower ALB levels than usual, and this decrease was significantly correlated with infection prognosis [20]. A significant reduction in ALB levels often indicates the severity and persistence of infection. In critically ill patients, low ALB levels are associated with malnutrition but also with severe acute inflammatory responses [21]. Typically, low ALB levels suggest widespread inflammation, which may signal a longer disease course or poorer prognosis. Thus, ALB serves as crucial warning indicator of infection, providing valuable insights into a patient's health status and infection severity. These findings align with several studies showing that low ALB levels are critical markers in infectious diseases. For example, in critically ill patients, ALB levels often drop significantly in cases of sepsis or other systemic infections, with low ALB levels correlating with both infection severity and poor prognosis [22]. In patients with chronic inflammatory diseases, a decline in ALB levels can serve as an early warning signal of impending infection [23].

CRP, an acute-phase reactant protein, significantly increases during infections or inflammatory responses. Our study found that CRP displayed trends similar to ESR and ALB in predicting infections, but its changes were more rapid and sensitive. CRP levels in patients with bacterial and viral infections were closely associated with infection onset, particularly during the acute phase, reflecting inflammatory responses within a short time frame. In severe infections, such as bacterial pneumonia and sepsis, CRP levels increased significantly, correlating with clinical symptoms and disease progression. Therefore, CRP is a valuable biomarker for infection diagnosis, offering clinicians faster and more accurate diagnostic information. Previous studies have confirmed the importance of CRP in acute-phase infections, particularly in sepsis and bacterial pneumonia, where CRP levels often exceed normal ranges and exhibit greater sensitivity than ESR or white blood cell count [24]. Additionally, CRP rises more quickly than other markers, providing timely alerts for clinicians in the early stages of bacterial infection [25].

When comparing different types of infection, the combination of ESR, ALB, and CRP demon-

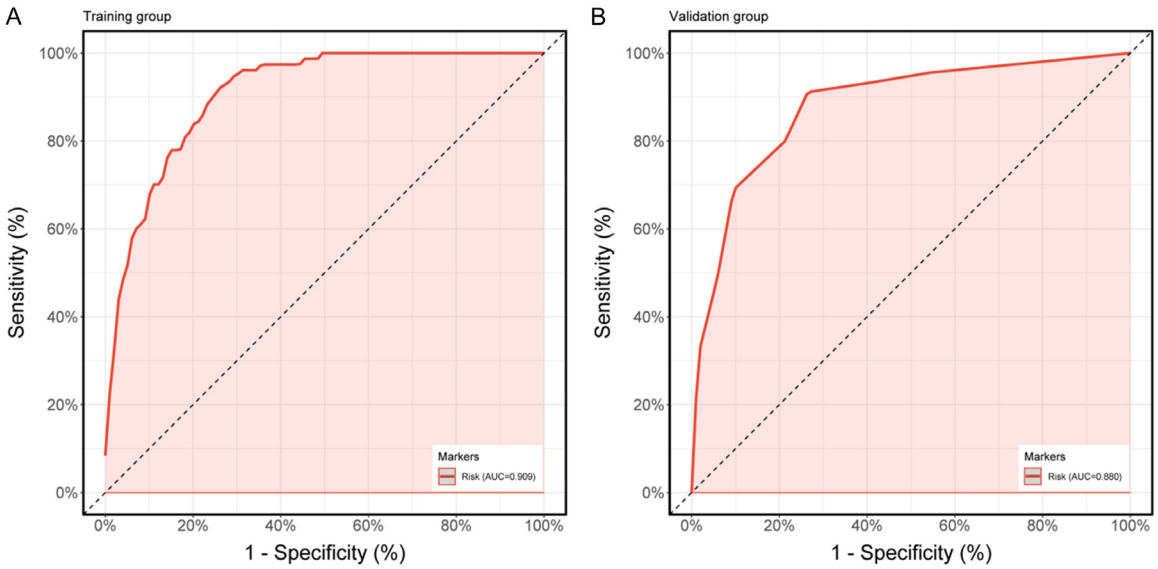

Figure 5. Comparison of ROC Curves for ALB + CRP + ESR model in the training and validation groups. A: ROC curve for the training group model. B: ROC curve for the validation group model. Note: ROC, receiver operating characteristic; AUC, area under curve; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

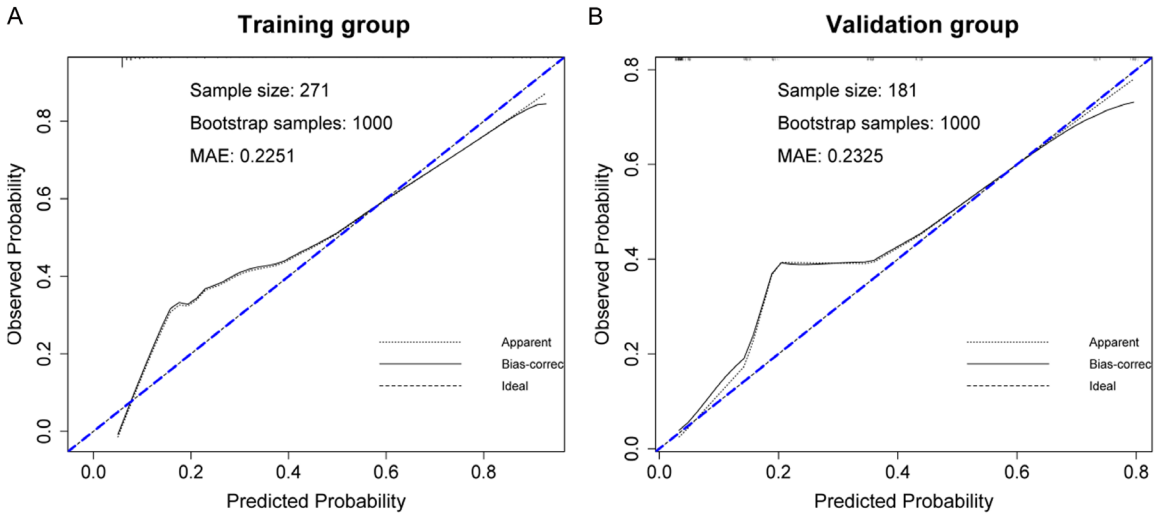

Figure 6. Calibration curves for models in the training and validation groups. A: Calibration curve for ALB + CRP + ESR model in the training group. B: Calibration curve for ALB + CRP + ESR model in the validation group. Note: MAE, mean absolute error; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

strated excellent clinical effectiveness in terms of sensitivity and specificity for infection prediction. Specifically, in distinguishing between bacterial and viral infections, changes in these three markers helped clinicians identify infection types earlier and select appropriate treatment strategies. For instance, ESR and CRP tend to rise simultaneously in bacterial infections, while ALB shows a decreasing trend, indicating a more severe infection response. In contrast, CRP elevation is typically more pronounced in viral infections, and ALB reduction is relatively milder. Literature supports this trend, particularly in the early stages of bacterial and viral infections. CRP changes often precede other markers, making CRP essential for early diagnosis [26]. In severe infections, ESR and CRP commonly increase together, while ALB reduction indicates infection severity [27]. Thus, combining these three markers provides

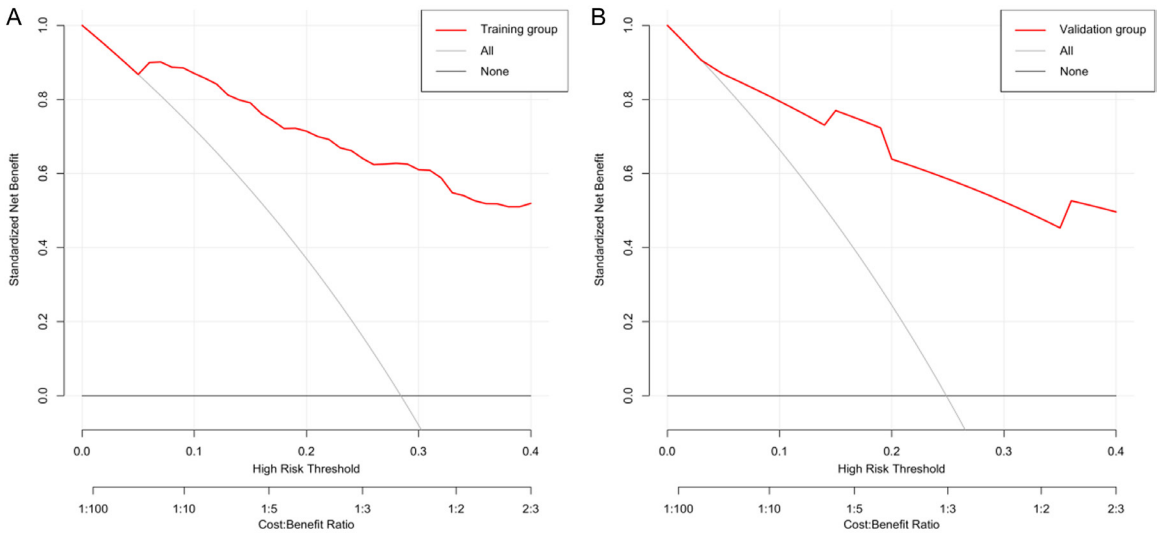

Figure 7. DCA curves for ALB + CRP + ESR model in the training and validation groups. A: DCA curve for ALB + CRP + ESR model in the training group. B: DCA curve for ALB + CRP + ESR model in the validation group. Note: DCA, decision curve analysis; ALB, albumin; CRP, C-reactive protein; ESR, erythrocyte sedimentation rate.

valuable clinical insights and aids in more accurate diagnostic decisions.

Despite the clinical significance of ESR, ALB, and CRP in predicting infections, this study has limitations. The sample size is relatively small and restricted to a single region, which may limit the external validity and generalizability of the findings. Additionally, the study focused exclusively on ESR, ALB, and CRP, without considering other potential factors that could influence infection prediction, such as other clinical symptoms or additional laboratory tests. Future research should aim to expand the sample size, include patients from diverse regions, and incorporate additional clinical indicators to improve the prediction accuracy.

Conclusion

This study underscores the clinical significance of ESR, ALB, and CRP in predicting infections, demonstrating that these markers are crucial for early infection detection. The combination of ESR, ALB, and CRP significantly enhances the accuracy of infection prediction, especially for bacterial and viral infections. These findings provide valuable insights into the early diagnosis of infections, with substantial clinical utility. However, further optimization of the prediction model, larger sample sizes, and multi-center validation are needed to ensure the reliability and generalizability of these results across diverse clinical settings.

Disclosure of conflict of interest

None.

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