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ORIGINAL RESEARCH

Related Risk Factors That Predict Moderate to Severe Asthma Attack in Children: Analysis Based on Logistic Regression and Decision Tree

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Purpose: To analyse the related risk factors of moderate to severe asthma attack in children by logistic regression and decision tree.

Patients and Methods: A retrospective analysis of clinical data of children diagnosed with asthma attacks in our hospital from January 2020 to August 2023 was conducted. The patients were divided into mild group (n=459, 57.02%) and moderate to severe group (n=346, 42.98%). Related risk factors of moderate to severe asthma attack in children were analyzed by univariate logistic regression, and then multivariate logistic regression and decision tree model were obtained.

Results: The results of univariate logistic regression showed that there were significant differences between the two groups in age, medical history, allergy history, family history, C-reactive protein (CRP), neutrophil percentage (NEU%), Mycoplasma pneumoniae (MP) infection, Rhinovirus (RV) infection (all $p < 0.05$). The results of multivariate logistic regression showed that age (≥6 years) (OR=1.636, 95% CI=1.046–2.559), medical history (OR=1.460, 95% CI=1.063–2.006), allergy history (OR=2.387, 95% CI=1.733–3.288), family history (OR=2.564, 95% CI=1.619–4.058), NEU% (OR=1.020, 95% CI=1.009–1.031), MP infection (OR=2.140, 95% CI=1.571–2.916), RV infection (OR=4.546, 95% CI=2.274–9.089) were related risk factors of moderate to severe asthma attack in children (all $p<0.05$). The decision tree model showed that MP infection, CRP, allergy history, NEU%, and medical history were risk factors of moderate to severe asthma attacks in children, with importance levels of 0.41, 0.29, 0.134, 0.130, and 0.061, respectively. Multivariate logistic regression (AUC=0.733, 95% CI: 0.698~0.767) and decision tree (AUC=0.694, 95% CI: 0.658~0.731) both exhibited good prediction accuracy.

Conclusion: Allergic history, medical history, MP infection, and increased NEU% were related risk factors that predict moderate to severe asthma attack in children. Multivariate logistic regression and decision tree both had a good predictive effect for analyzing the risk factors of moderate to severe asthma attack in children.

Keywords: moderate to severe attack, childhood asthma, logistic regression, decision tree, risk factors

Introduction

Asthma is a specific disease characterized by chronic airway inflammation and airway hyperresponsiveness, and is the most common chronic inflammatory airway disease in children.[1,2] Recurrent coughing, wheezing, shortness of breath, and chest tightness are common clinical symptoms of asthma, which usually attack or deteriorate at night or in the morning.[3–5] A recent survey of adult asthma in China showed that the prevalence of asthma in people aged ≥20 years was as high as 4.2%, which was much more than previous prediction.[3] Therefore, it can be inferred that the prevalence of childhood asthma in China may be higher than current predicted value as well. The Global Initiative for Asthma (GINA) reported that there were nearly 300 million asthma patients globally by 2024.[6] In 2025, a meta-analysis showed that the overall prevalence of childhood asthma in the world reached 10.2%.[7] Great progress has been made in diagnosing and

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treating of childhood asthma in China recently; however, more than 20% of children's asthma cannot be controlled well.[8] Asthma attacks, especially moderate to severe attacks, have a major impact on physical and mental health of children. Moreover, it even endangers children lives and imposes a huge burden on family and society.[2,9] Thus, early identification of risk factors for moderate to severe asthma attacks is important for preventing severe asthma attacks and improving quality of life.

There were some studies on the influence factors of asthma attacks in children in recent years,[7,8] but few studies based on machine learning methods. Logistic regression is a statistical model used to calculate the probability of categorical variables and it can predict clinical outcomes by analyzing the linear relationship among variables.[10] The decision tree model segments data through established rules and then plot a tree-structure diagram, which has an advantage of displaying the characteristics of each factor in the decision tree and identifying high-risk populations.[11,12] This study combined traditional statistical methods (logistic regression) with machine learning techniques (decision tree analysis) to identify and predict risk factors for moderate to severe asthma attacks in children. This dual approach enhances understanding by capturing both linear relationships and complex interactions among variables.

To sum up, this study retrospectively analyzed the data of pediatric in-patients with asthma attacks, and then logistic regression and decision tree were applied to analyze the related risk factors of moderate to severe asthma attacks in children. The aim of this paper was to identify the risk factors of moderate to severe asthma attacks in children to prevent severe asthma cases. Meanwhile, the study explored new analysis approaches by combining logistic regression with machine learning techniques (decision tree model) for influence factors on asthma attacks in children.

Materials and Methods

Study Population

The data of 914 children diagnosed with asthma attack in Chengdu Women's and Children's Central Hospital from January 2020 to August 2023 was collected. One hundred and nine patients were excluded according to the inclusion and exclusion criteria, and the remaining 805 were divided into mild group (n=459, 57.02%) and moderate to severe group (n=346, 42.98%) according to the Chinese "Guidelines for Diagnosis and Prevention of Children's Bronchial Asthma (2016)",[2] as shown in Figure 1. The studies involving human participants were reviewed and approved by The ethics board of Chengdu Women and Children Center Hospital (Ethical number: [2021] 203). Written informed consent to participate in this study was provided by the participants' legal guardian.

Inclusion Criteria: 1. Patients who meet the diagnostic criteria for asthma attacks in the Chinese "Guidelines for the Prevention and Treatment of Bronchial Asthma (2016)";[2] The classification criteria for the severity of asthma attacks in children were shown in Tables 1 and 2. 2. Patients with complete case data.

Exclusion criteria: 1. Patients with asthma in chronic persistence or clinical remission; 2. Patients with congenital malformations of cardiopulmonary development such as bronchopulmonary dysplasia, congenital heart disease, and pulmonary vascular malformations; 3. Patients with a combination of other respiratory conditions such as airway obstruction, lung tumor and lung injury; 4. Patients with a combination of severe cardiac, hepatic, renal and other vital organ insufficiency.

Methods

Collection of Clinical Data

The clinical data of the patients was collected by the electronic pathology system. These data included General data (gender, age, diagnosis), medical history (history of allergic diseases such as urticaria, eczema and atopic dermatitis et al), allergy history (allergic history of food, medication, or others), family history (family history of allergic diseases), respiratory pathogen examination, sputum culture, and inflammatory index such as neutrophil percentage (NEU%), C-Reactive Protein (CRP), Procalcitonin (PCT). And then, a retrospective analysis was conducted on the clinical data mentioned above.

Respiratory Pathogen Examination

Nasopharyngeal swabs were collected on the day the patient was admitted to the hospital, and then detected by real-time fluorescent PCR by using Hunan Shengxiang biological kits for pathogens, including Mycoplasma Pneumoniae (MP), Respiratory Syncytial Virus (RSV), Rhinovirus (RV), influenza A virus, influenza B virus, adenovirus.

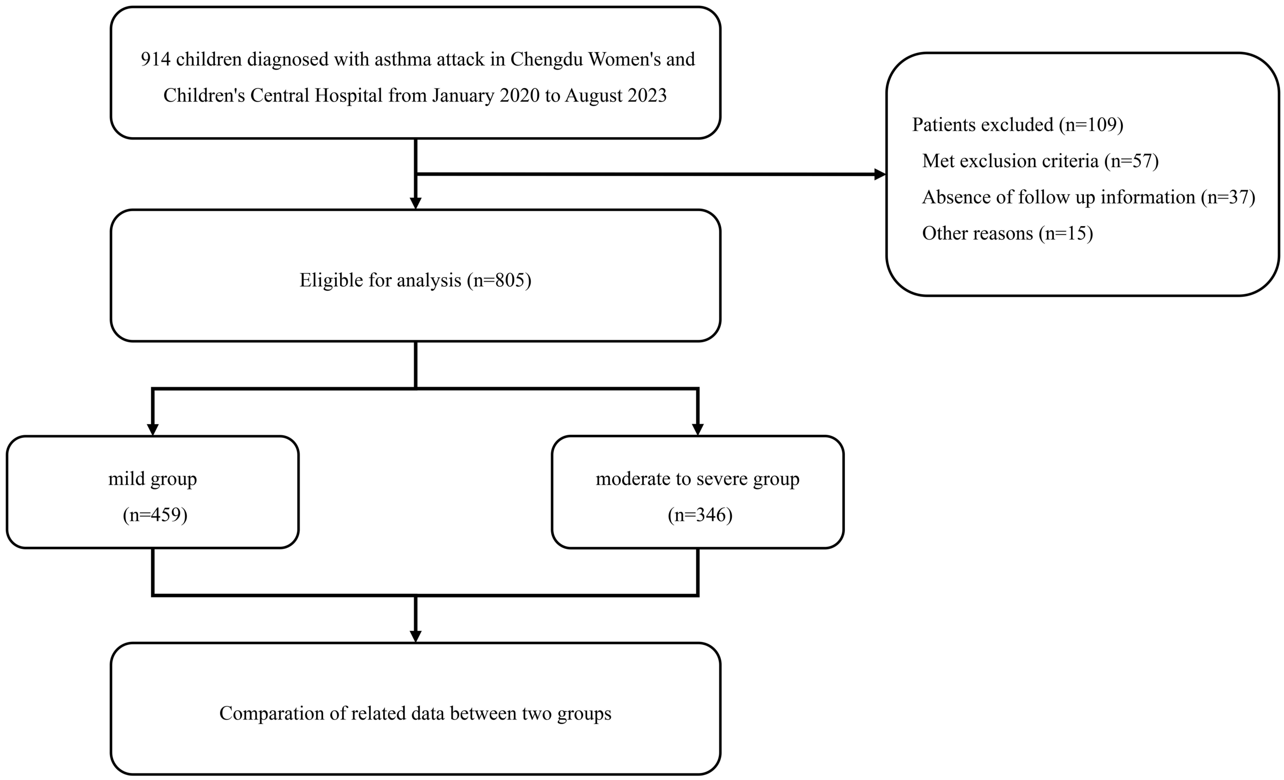

Figure 1 Flowchart of patients enrollment and exclusion.

Sputum Culture

Nasopharyngeal aspirates were taken by aseptic negative pressure on the day of admission of patients and then sent for sputum culture examination (bacterial culture as the detection standard).

Table 1 Classification of Severity of Asthma Attacks in Children Aged ≥6 years[2]

Clinical Characteristics	Mild	Moderate	Severe	Super Severe
Shortness of breath	While walking	While talking	While resting	Respiratory distress
Posture of body	Can lie flat	Sitting position	Forward-leaning position	Unstable
Way of speaking	Complete sentences	Short sentences	Single words	Cannot speak
Mental state	Anxious and restless	Frequent anxiety and restlessness	Constant anxiety and restlessness	Drowsiness, impaired consciousness
Auxiliary respiratory muscle activity and three-concave sign	Absent	Present	Usually-present	Chest and abdominal paradoxical movement
Wheezing sound	Scattered, at the end of expiration	Loud, diffuse	Loud, diffuse, bilateral	Weakened or even disappeared
Pulse rate	Slightly increased	Increased	Significantly increased	Slow or irregular
PEF% of normal predicted value or personal best value (%)	>80 after SABA treatment	>50~80 before SABA treatment; >60~80 after SABA treatment	≤50 before SABA treatment; ≤60 after SABA treatment	Cannot measure
SPO_2 (inhaled air)	0.90–0.94	0.90–0.94	0.90	<0.90

Notes: When judging the severity of an acute asthma attack, as long as there are indicators meeting the criteria for a certain severity level, it can be classified into that severity level.
Abbreviations: SPO_2, blood oxygen saturation; PEF, Peak expiratory flow; SABA, Short-acting β_2 agonist.

Table 2 Classification of Severity of Asthma Attacks in Children Aged <6 years[2]

Clinical Characteristics	**Mild**	**Severe**
Mental state change	None	Anxiety, restlessness, drowsiness, or confusion
SPO_2 (inhaled air)	≥ 0.92	< 0.92
Way of speaking	Can speak in complete sentences	Can only say single words
Pulse rate	< 100	> 200 (0~3 years old) > 180 (4~5 years old)
Cyanosis	None	May be present
Wheezing sound	Absent	Weakened or even disappeared

Notes: When judging a severe attack, as long as one item meets the criteria, it can be classified into this severity level.
Abbreviation: SPO_2, blood oxygen saturation.

Sample Size

Logistic regression requires that the number of events of each kind in the dependent variable to be at least 5–10 times greater than the total number of independent variables included in the study.[13] The larger the sample size used by the decision tree model, the better. There is no minimum sample size.[14] There are 15 independent variables in this study, and the dependent variables are both more than 150 cases. Therefore, the sample size of the research object meets the conditions.

Statistical Analysis

Data analysis was performed by SPSS 26.0 statistical software. Risk factors were screened by univariate logistic regression, and then factors with significant differences in the univariate analysis were regarded as independent variables. These variables were included in the multivariate logistic regression and decision tree models for analysis respectively. The Chi squared automatic interaction detector (CHAID) method was used for decision tree analysis, and the model was validated by stratified ten-fold cross method. Set the maximum number of growth layers to 3, the minimum sample size of the parent node to 100, and the minimum sample size of the child node to 50. The significance level of growth branch segmentation was α=0.05. p<0.05 was considered statistically significant. The receiver operating characteristic (ROC) curve was plotted and the area under curve (AUC) was calculated to assess the predictive effect of each model. The importance of variables in the decision tree model was calculated by IBM SPSS Modeler 18.0 software.

Results

The severity of asthma attacks was regarded as the dependent variable, and the factors such as gender, age, medical history, allergy history, family history, CRP, PCT, NEU%, and pathogen infections (MP, RSV, RV, influenza A virus, influenza B virus, adenovirus, and sputum cultures) were regarded as the independent variables. Dichotomous variables among them were assigned dichotomous values, as shown in Table 3. The factors with statistical differences in univariate logistic analysis were regarded as independent variables in multivariate logistic regression analysis and decision tree model.

Table 3 Assignment of Dichotomous Variables

Variable	**Variable Assignment**
Asthma attack	Mild attack = 0, Moderate to severe attack =1
Gender	Male = 0, Female = 1
Age	<6 years = 0, ≥6 years = 1
Medical history	Negative = 0, Positive = 1

(*Continued*)

Table 3 (Continued).

Variable	Variable Assignment
Allergy history	Negative = 0, Positive = 1
Family history	Negative = 0, Positive = 1
MP infection	Negative = 0, Positive = 1
RSV infection	Negative = 0, Positive = 1
RV infection	Negative = 0, Positive = 1
Influenza A virus infection	Negative = 0, Positive = 1
Influenza B virus infection	Negative = 0, Positive = 1
Adenovirus infection	Negative = 0, Positive = 1
Sputum cultures	Negative = 0, Positive = 1

Abbreviations: MP, Mycoplasma Pneumoniae; RSV, Respiratory Syncytial Virus; RV, Rhinovirus.

Univariate Logistic Regression Analysis

The relationship between the factors above and the severity of asthma attack was analyzed ($p<0.05$ was considered statistically significant) as shown in Table 4. The results suggested that there was a statistically significant difference between the moderate to severe group and the mild group in terms of age, medical history, allergy history, family history, CRP, NEU%, MP infection, and RV infection (all $p<0.05$).

Table 4 Univariate Logistic Regression Analysis of the Related Factors

Related Factors	B	SE	Waldχ2	p	OR	95% CI
Gender	0.177	0.135	1.725	0.189	1.193	0.917~1.554
Age	0.884	0.198	20.006	0.000	2.421	1.643~3.567
Medical history	0.548	0.138	15.731	0.000	1.730	1.320~2.269
Allergy history	0.860	0.142	36.809	0.000	2.363	1.790~3.119
Family history	0.886	0.201	19.482	0.000	2.426	1.637~3.595
CRP	0.023	0.008	7.726	0.005	1.023	1.007~1.040
PCT	−0.032	0.309	0.011	0.916	0.968	0.529~1.773
NEU%	0.027	0.005	34.860	0.000	1.028	1.018~1.037
MP infection	0.798	0.137	33.903	0.000	2.220	1.697~2.904
RSV infection	0.523	0.286	3.358	0.067	1.688	0.964~2.954
RV infection	1.540	0.327	22.198	0.000	4.664	2.458~8.849
Influenza A virus infection	−1.015	0.655	2.401	0.121	0.362	0.100~1.309
Influenza B virus infection	0.515	0.255	3.401	0.061	1.362	0.906~2.309
Adenovirus infection	−0.397	0.617	0.414	0.520	0.673	0.201~2.252
Sputum cultures	−0.035	0.152	0.053	0.819	0.966	0.717~1.301

Abbreviations: CRP, C-Reactive Protein; PCT, Procalcitonin; NEU%, Neutrophil percentage; MP, Mycoplasma Pneumoniae; RSV, Respiratory Syncytial Virus; RV, Rhinovirus; B, Regression coefficient; SE, Standard Error; OR, Odds Ratio; 95% CI, 95% confidence intervals.

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Table 5 Multivariate Logistic Regression Analysis of the Related Factors

Related Factors	B	SE	Waldχ2	p	OR	95% CI
Age	0.492	0.228	4.648	0.031	1.636	1.046~2.559
Medical history	0.378	0.162	5.449	0.020	1.460	1.063~2.006
Allergy history	0.870	0.163	28.364	0.000	2.387	1.733~3.288
Family history	0.941	0.234	16.130	0.000	2.564	1.619~4.058
CRP	0.003	0.009	0.093	0.761	1.003	0.985~1.021
NEU%	0.020	0.006	13.075	0.000	1.020	1.009~1.031
MP infection	0.761	0.158	23.287	0.000	2.140	1.571~2.916
RV infection	1.514	0.353	18.355	0.000	4.546	2.274~9.089

Abbreviations: CRP, C-Reactive Protein; NEU%, Neutrophil percentage; MP, Mycoplasma Pneumoniae; RV, Rhinovirus; B, Regression coefficient; SE, Standard Error; OR, Odds Ratio; 95% CI, 95% confidence intervals.

Multivariate Logistic Regression Analysis

The results of multivariate logistic regression analysis are shown in Table 5. The results indicated that age (≥6 years) (OR=1.636, 95% CI=1.046–2.559), medical history (OR=1.460, 95% CI=1.063–2.006), allergy history (OR=2.387, 95% CI=1.733–3.288), family history (OR=2.564, 95% CI=1.619–4.058), NEU% (OR=1.020, 95% CI=1.009–1.031), MP infection (OR=2.140, 95% CI=1.571–2.916), RV infection (OR=4.546, 95% CI=2.274–9.089) were independent risk factors of moderate to severe asthma attack in children (all p<0.05). However, there were no significant differences in CRP between two groups.

Decision Tree Model of Asthma Attack Severity

The results of decision tree model are shown in Figure 2. The model tree size was 14, with 4 layers and 8 leaves. Allergy history was the first variable in the decision tree, serving as the root node. MP infection, NEU%, CRP, and medical

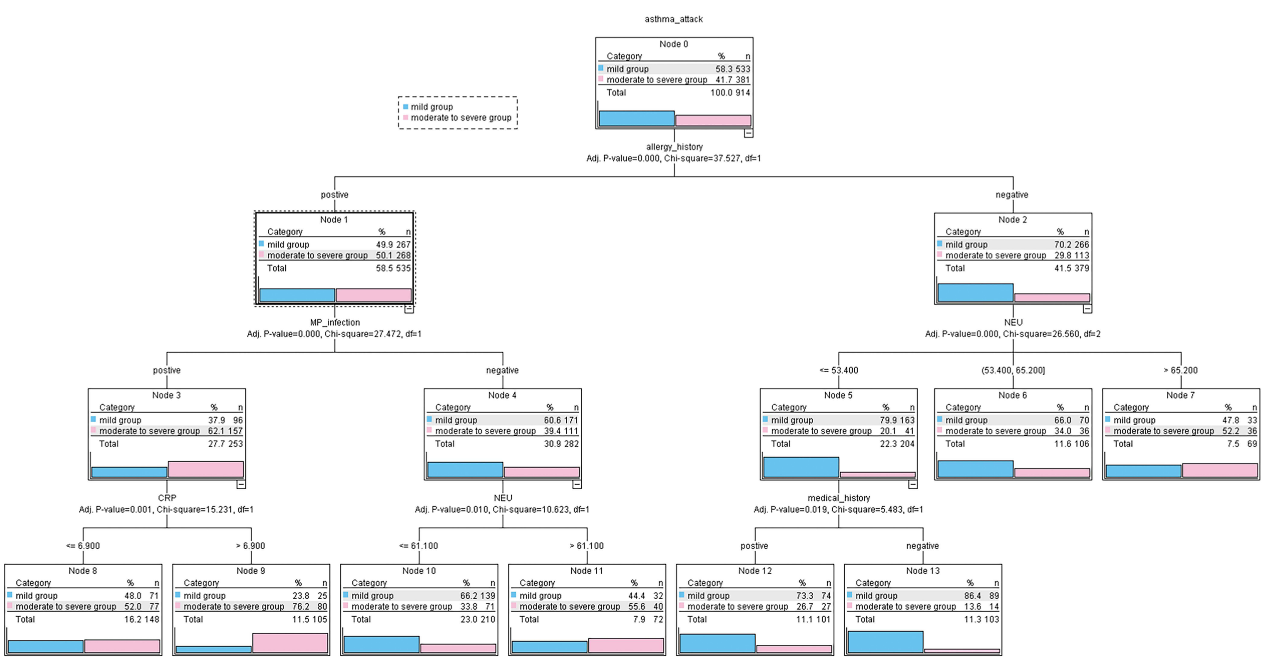

Figure 2 Decision tree model of asthma attack severity.
Abbreviations: CRP, C-Reactive Protein; MP, Mycoplasma Pneumoniae; NEU%, Neutrophil percentage.

Table 6 Eight Rules in Decision Tree Analysis

Related Factors	Predicted Incidence Rate
IF Allergy history = Positive AND MP = Positive AND CRP ≤ 6.9mg/L, THEN Result = "1"	52.03%
IF Allergy history = Positive AND MP = Positive AND CRP > 6.9 mg/L, THEN Result = "1"	76.19%
IF Allergy history = Positive AND MP = Negative AND NEU% ≤61.1%, THEN Result = "1"	33.81%
IF Allergy history = Positive AND MP = Negative AND NEU% >61.1%, THEN Result = "1"	55.56%
IF Allergy history = Negative AND NEU% ≤53.4% AND Medical history = Positive, THEN Result = "1"	26.73%
IF Allergy history = Negative AND NEU% ≤53.4% AND Medical history = Negative, THEN Result = "1"	13.59%
IF Allergy history = Negative AND 53.4% <NEU% ≤65.2%, THEN Result = "1"	33.96%
IF Allergy history = Negative AND NEU% > 65.2%, THEN Result = "1"	52.17%

Notes: 1, moderate to severe attack of asthma; 0, Mild attack of asthma.
Abbreviations: CRP, C-Reactive Protein; MP, Mycoplasma Pneumoniae; NEU%, Neutrophil percentage.

history were the child nodes. The average model prediction accuracy was 66.2%. Eight rules were formed, as shown in Table 6. The rules indicated that: 1. The probability of moderate to severe asthma attacks in children with allergy history and MP infection was 52.03% when CRP ≤ 6.9 mg/L, but 76.19% when CRP > 6.9 mg/L. Therefore, the higher the CRP, the higher the risk of a moderate to severe asthma attack. 2. The probability of moderate to severe asthma attacks in children with allergy history and without MP infection was 33.81% when NEU%≤61.1%, but 55.56% when NEU% >61.1%. Therefore, the higher the NEU%, the higher the risk of a moderate-to-severe asthma attack. 3. The probability of moderate to severe asthma attacks in children with NEU% ≤53.4% and without allergy history was 13.59% when the medical history was negative, but 26.73% when the medical history was positive. Therefore, the higher the risk of developing moderate to severe seizures with a positive medical history. 4. The probability of moderate to severe asthma attacks in children without allergy history was 33.96% when t53.4%<NEU% ≤65.2%, but 52.17% when NEU% >65.2%. Therefore, the higher the NEU%, the higher the risk of a moderate-to-severe asthma attack. The importance of each node in the decision tree was MP infection (0.41)> CRP (0.29) > allergy history (0.134) > NEU% (0.130) > medical history (0.061), as shown in Figure 3.

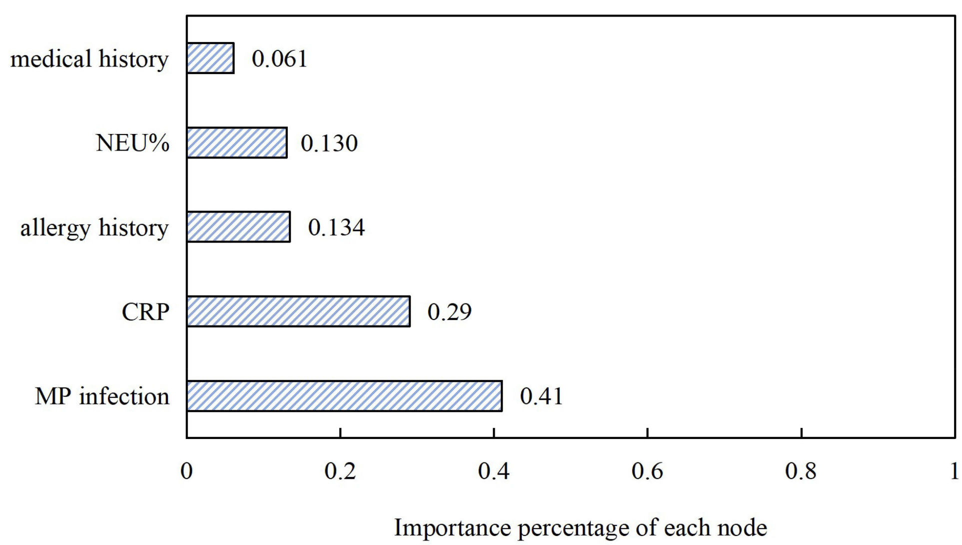

Figure 3 The importance of each node in the decision tree.
Abbreviations: CRP, C-Reactive Protein; MP, Mycoplasma Pneumoniae; NEU%, Neutrophil percentage.

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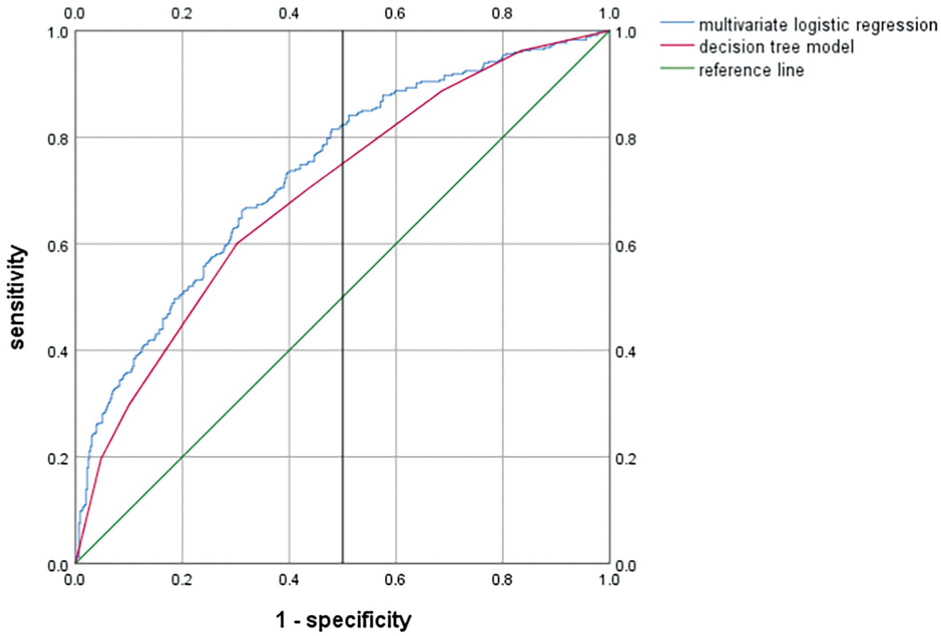

Figure 4 ROC curves of multivariate logistic regression and decision tree model.

Comparison of Multivariate Logistic Regression and Decision Tree Model

The predicted values of multivariate logistic regression and decision tree were used as state variables to plot the ROC curves, as shown in Figure 4. The AUCs of the logistic regression and decision tree models were 0.733 and 0.694 respectively, and both of them had a good predictive effect, as shown in Table 7.

Discussion

Asthma is the most common chronic respiratory disease in children. In recent 20 years, the incidence rate of childhood asthma in China has shown an obvious upward trend. Epidemiological survey showed that the prevalence rate of childhood asthma in urban China was 3.02% and the overall control level was still unsatisfactory.[2,15] Asthma attacks are characterized by a progressive exacerbation process and a reduction in expiratory flow rate, and it is often triggered by allergens, irritants or respiratory infections. Furthermore, asthma attacks, especially moderate and above attacks, have effect on the physical health of children, which may lead to respiratory failure and even danger to life.[15,16] Therefore, this study analyzed the related risk factors for moderate to severe asthma attacks in children in order to provide reference for preventing and reducing the severe asthma attack.

More and more researchers applied the machine learning methods in clinical study in recent years. However, few of them have applied it to the study of the influence factors of asthma attacks. Therefore, logistic regression and decision tree were used in this study. We found that age (≥6 years), medical history, allergy history, family history, NEU%, MP infection, and RV infection were screened as independent risk factors for moderate to severe attacks of asthma in children by univariate and multivariate logistic regression analysis.

Table 7 Comparison of Multivariate Logistic Regression and Decision Tree Model

Statistical Model	AUC	SE	p	95% CI
Multivariate logistic regression	0.733	0.018	0.000	0.698~0.767
Decision tree model	0.694	0.019	0.000	0.658~0.731

Abbreviations: AUC, Area Under Curve; SE, Standard Error; 95% CI, 95% confidence intervals.

1. Age (≥6 years) is an independent risk factor for moderate to severe asthma attacks in children, which may be due to the increased probability of respiratory infections and allergen exposure in children age (≥6 years) caused by school attendance and outdoor activities.[17] It could also be because parents may not be able to supervise treatment well due to children's self-awareness. There were other reasons, such as medication dosage reduction or stopping due to the prolonged use of medication.[18] Xu et al[19] found that compared to children (<6 years), children (≥6 years) were more likely to be exposed to triggering factors such as exercise, emotional changes, dust, pollen, home decoration, mosquito coils, and pets. Therefore, this may be more likely to lead to moderate to severe asthma attacks in children (≥6 years).
2. Medical history, allergy history, and family history were related risk factors for moderate to severe asthma attacks in children, increasing the risk of developing asthma.[1,2] Zhao et al[20] and Xu et al[19] found that medical history of allergic diseases, allergy history, and family history of allergic diseases were risk factors for poor asthma control and acute attacks. It had been reported that the medical history of allergic diseases such as atopic dermatitis, eczema and allergic rhinitis could also increase the risk and severity of asthma attacks.[21]
3. Asthma is a chronic inflammatory disease of the airways, in which various inflammatory cells and cytokines are involved in the pathogenesis of asthma.[1,2] The Global Initiative for Asthma (GINA) in 2023 suggested that most of the asthma belongs to type II inflammation.[22] Previous studies mostly focused on the role of eosinophils (EOS) in the pathogenesis of asthma. EOS were involved in asthmatic airway type II inflammation, causing airway hyperresponsiveness.[23] On the other hand, our study found that an increase in NEU% was also a related risk factor for moderate to severe asthma attacks. NEU damaged the airways by releasing cytokines such as IL-1, IL-6, IL-8, TFN, TGF-β and by mobilizing B and T cells, leading to an immune imbalance.[24] The concentration of neutrophil extracellular traps (NETs) formed by NEU increased in asthma patients, and the more severe the asthma attack, the higher the concentration of NETs.[25] Excessive accumulation of NEU in airway might lead to a burst of inflammation or delayed resolution and result in asthma attacks, especially moderate to severe attacks and even asthma persistence.[26] It was found that NEU% in peripheral blood were significantly increased during an asthma attack in children and the NEU% increased more in children with severe asthma than that in the non-severe group, suggesting that increased peripheral blood NEU% were associated with asthma attacks, especially with severe attacks.[27,28] The above research results were consistent with our study.
4. We found that MP infection and RV infection were related risk factors for moderate to severe asthma attacks. MP is one of the most common respiratory pathogens in children.[29] MP can cause chronic airway inflammation by adhering, colonizing and invading host cells, destroying airway epithelium and movement of cilia. MP can also induce airway hyperresponsiveness by mediating an abnormal immune response, leading to asthma attacks.[30] A retrospective study found that patients in asthma attack group had a higher proportion of MP infection compared to the control group, suggesting that MP infection was associated with asthma attacks.[31] Biscardi et al[32] found that among the patients previously diagnosed with asthma, 20% of whom with severe asthma attacks had MP infection. Among the patients diagnosed with asthma for the first time, 50% of severe asthma patients were accompanied by MP infection, indicating that MP infection may be closely related to the severity of asthma attacks. As is well known, respiratory viral infections are the most important trigger for asthma attacks. A study of risk factors for children with asthma attacks in Chongqing found that 85% of them were caused by respiratory viral infections.[33] RV (48%) were found to be the most common pathogen in asthma attacks, which were significantly associated with inadequate control and exacerbation of asthma.[34] It was reported that C-type RV infection can easily lead to more severe asthma attacks.[35,36] The studies above indicated that MP and RV infections were closely related to asthma attacks, especially severe cases. The above research results were consistent with our study.

Decision tree is a model to classify the data by segmenting data features from top to bottom and by selecting the best features as segmentation points based on set criteria. The set criteria were moderate to severe asthma attacks in this study.[11,37] A decision tree model was constructed to predict moderate to severe asthma attacks in children based on univariate logistic regression in this study, and then hierarchical decisions from the root node to the child node were made to obtain the predicted risk factors ultimately. This model showed that MP infection, CRP, allergy history, NEU%, and medical history were risk factors of moderate to severe asthma attacks in children, with importance levels of 0.41, 0.29, 0.134, 0.130, and 0.061, respectively. Among them, MP infection was the most relevant factor, suggesting that clinical attention should be paid to the children with asthma and MP infection and we should be vigilant for the occurrence of moderate to severe or above asthma attack. Compared to multivariate logistic regression, the decision tree included CRP as a predictor of moderate to severe asthma attacks. CRP is an acute reactive protein that reflects the level of inflammation and tissue damage. Zhang Yun et al[38] found that the CRP levels of the control group, allergic induced asthma attacks, viral induced asthma attacks, and bacterial induced asthma attacks were 0–2 mg/L, 2–10 mg/L, 5–16 mg/L, and ≥16 mg/L, respectively, indicating that CRP levels were related to the triggers of asthma attacks. Researches stated that CRP levels were higher in the moderate to severe attack group than that in the mild attack group,[39] which was consistent with our study. However, variables with significance in multifactorial logistic regression such as age, family history, and RV infection were not included in the decision tree, probably due to the influence of the depth of the decision tree and the sample size of each node.

The reason for the differences of the results in decision tree and logistic regression was because logistic regression can better fit the overall linear relationship, but it was difficult to solve the problem of collinearity of variables and was also susceptible to the influence of extreme values. On the other hand, the decision tree adopts a segmented validation method, focusing on gaining a deeper understanding of the details of the data and deriving prediction probabilities. Therefore, there were some differences between the results of logistic regression and decision tree models in practical applications.[40] To avoid overfitting the model, the AUC was used to test the predictive accuracy. The result showed that multivariate logistic regression (AUC=0.733, 95% CI: 0.733~0.767) and the decision tree (AUC=0.694, 95% CI: 0.694~0.731) had a good predictive efficacy. Thus, both of the predictive models can be combined for analyzing the influence factors of asthma attacks.

The standardized diagnosis and treatment recommendations for childhood asthma (2020 edition)[1] suggested that environmental pollutants, especially fine particulate matter (PM) 2.5 could exacerbate asthma symptoms and increase the risk of attacks and hospitalization. However, the effect of environmental pollutants on asthma attacks was not discussed in this study and would be further explored in subsequent studies. On the other hand, the ADM33 (A Disease and Metalloprotease 33) gene is located on the short arm p13 of chromosome 20 and it belongs to the ADAM superfamily. It is an important susceptibility gene for asthma.[41] Blocking the expression of ADM33 may prevent the occurrence of asthma.[42] Some studies stated that the expression of ADM33 gene was highest in severe asthma group, intermediate in mild group, and lowest in healthy group.[43] Additionally, Th2 (T helper 2) related genes and Th17 (T helper 17) related genes were closely associated with asthma.[44–46] The pathophysiology of allergic airway inflammation was thought to be shaped mainly by Th2 cells. The impact of the Th2 cytokines, such as IL-4, IL-5, and IL-13, had been revealed in human asthma, as well as in murine models of allergic airway inflammation.[44] Consistently, single-cell RNA sequencing identified an enrichment of a pathogenic Th2 in house dust mite-allergen-reactive asthma patients.[45,47] Th17 cells and Th17 cytokines played an important role in the pathological process of asthma, especially in severe asthma.[46] Saleh Al-Muhsen et al[48] found that Th17 cytokines increased airway hyper-responsiveness (AHR) by enhancing the TGF-β and IL-11 production from eosinophil in asthmatics. Moreover, Th17 cytokines worsened airway inflammation by activating neutrophils.[49] However, our study had not yet included the impact of multiple genetic polymorphisms in genes such as ADAM33, Th2-related genes, Th17-related genes on asthma attacks, and we will conduct further research in the future.

Conclusion

In conclusion, based on multivariate logistic regression and decision tree analysis, allergic history, medical history, MP infection, and increased NEU% were related risk factors that predict moderate to severe asthma attack in children. Therefore, children with the above risk factors need to be paid more attention in clinical work and being alert to moderate to severe asthma attacks in the children above is necessary. Early identification and prediction of risk factors can prevent severe asthma attacks and improve quality of life. Moreover, the multiple logistic regression and decision tree model had a good predictive effect in analyzing the risk factors of moderate to severe asthma attacks in children. Both methods are complimentary and could be applied together to provide a new approach for exploring the influence factors of childhood asthma attacks in clinical work.

However, the limitations of this study were as follows. Firstly, the moderate predictive accuracy of the decision tree (66.2%) was reasonable though not high, given the complexity of asthma attacks and clinical variability. Secondly, the study result was not generalizable to other settings because the asthma classification was based on Chinese criteria. We will continue to modify our analysis methods to improve the predictive accuracy and collect more data from different regions based on possible international project for further research.

Abbreviations

CRP, C-Reactive Protein; PCT, Procalcitonin; NEU%, Neutrophil percentage; MP, Mycoplasma Pneumoniae; RSV, Respiratory Syncytial Virus; RV, Rhinovirus; B, Regression coefficient; SE, Standard Error; OR, Odds Ratio; 95% CI, 95% confidence intervals; AUC, Area Under Curve; SPO_2, blood oxygen saturation; PEF, Peak expiratory flow; SABA, Short-acting β_2 agonist; ADM33, A Disease and Metalloprotease 33; Th2, T helper 2; Th17, T helper 2.

Ethics and Consent Statements

The ethics board of Chengdu Women and Children Center Hospital (Ethical number: [2021]203). Written informed consent to participate in this study was provided by the participants' legal guardian. The study complied with the Declaration of Helsinki.

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Disclosure

The authors report no conflicts of interest in this work.

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