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# Applications of machine learning approaches for pediatric asthma exacerbation management: a systematic review

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## Abstract

**Background** Pediatric asthma is a common chronic respiratory disease worldwide, and its acute exacerbation events significantly impact children's health and quality of life. Machine learning, an advanced data analysis technique, has shown great potential in healthcare applications in recent years. This systematic review aims to assess the application of ML techniques in pediatric asthma exacerbation and explore their effectiveness and potential value.

**Methods** Studies from four electronic databases, including PubMed, EBSCO, Elsevier, and Web of Science, from Jan 2000 to Jan 2025, were searched. Studies applying the ML methods for pediatric asthma exacerbation and published in English were eligible. The risk of bias and applicability of the included studies was assessed using the Effective Public Health Practice Project (EPHPP) quality assessment tool.

**Results** A total of 23 studies were selected for inclusion in this review, covering different ML models such as decision trees, neural networks, and support vector machines. These studies focused on analyzing risk factors for asthma exacerbation, diagnosing and predicting, optimizing and allocating healthcare resources, and comprehensive asthma management. The results show that ML techniques have significant advantages in the application of pediatric asthma exacerbation and in the provision of personalized health care.

**Conclusions** ML techniques show great promise for application in pediatric asthma exacerbations. With further research and clinical validation, these techniques are expected to provide strong support for diagnosis, personalized treatment, and long-term management of pediatric asthma exacerbation.

**Clinical trial number** Not applicable, Prospero registration number CRD42024559232.

**Keywords** Asthma Attack, Asthma deterioration, Asthma exacerbations, Machine learning, Pediatric asthma

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## Background

Asthma is one of the most common chronic respiratory diseases and has a significant impact on sufferers and their families. The symptoms of asthma include coughing, wheezing, chest tightness and shortness of breath. These symptoms vary from person to person, ranging from mild to severe, and may occur frequently or infrequently. An asthma exacerbation occurs when these symptoms worsen [1, 2]. Asthma exacerbation in adolescents and children aged 6–11 years according to the 2024 Global Strategy for Asthma Management and Prevention guidelines is defined as follows: Exacerbations of asthma are episodes characterized by a progressive increase in symptoms of shortness of breath, cough, wheezing or chest tightness and progressive decrease in lung function. Exacerbations may occur in patients with a preexisting diagnosis of asthma or, occasionally, as the first presentation of asthma. Among other things, the guidelines defined asthma exacerbation in children under 5 years of age as an acute or sub-acute deterioration in symptom control that is sufficient to cause distress or risk to health and necessitates a visit to a healthcare provider or requires treatment with systemic corticosteroids [3]. These exacerbations often result in school absences, parental absenteeism, unplanned emergency department (ED) visits, and hospitalizations, severely affecting the health-related quality of life (HRQL) of children and their parents [4]. Despite interventions, nearly half of pediatric asthma patients experience exacerbations annually, with 1/6 requiring ED visits and 1/20 hospitalization. These visits account for over 1.8 million ED visits and more than 60% of the total cost of asthma care [5–8].

In recent years, the use of machine learning (ML) algorithms in pediatric asthma exacerbations has shown significant potential. ML algorithms can assist physicians in more accurately diagnosing asthma by analyzing clinical data, such as electronic health records (EHRs), and pulmonary function test results, as well as predicting the risk of asthma exacerbations by integrating multiple sources of data, including clinical indicators, environmental factors, and socioeconomic factors [9–31]. It also provides patients with more personalized and precise medical services through its unique ability to process and analyze large and complex datasets and capture highly nonlinear relationships and complex interactions in the data [32–35]. However, there is still a lack of systematic review on the applications of ML in pediatric asthma exacerbation management.

This study aims to comprehensively analyze the current research progress of ML techniques in pediatric asthma exacerbation management, identify the critical risk factors, evaluate the effectiveness of these techniques, and explore the potential applications of ML in the diagnosis and prediction of pediatric asthma exacerbations, personalized treatment, and long-term health management. The knowledge synthesis from this study may provide a scientific basis for clinical decision-making, policy formulation, and health education, potentially improving the quality and efficiency of care in the future.

## Methods

### Search strategy

This systematic review complies with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards. Institutional review board approval was not required, as publicly available data were used and no human subjects were involved. A comprehensive search was performed in PubMed, EBSCO, Elsevier, and Web of Science, covering the period from January 2000 to January 2025. Studies published before 2000 were ineligible since they were considered less relevant to modern asthma care [36]. The search strategy was centered around the terms "Asthma," "Asthma exacerbation/attack/deterioration," and "Machine learning/Deep learning" and included their appropriate derivatives and synonyms such as "Asthmas" OR "Bronchial Asthma" OR "Asthma, Bronchial", "Learning, Machine" OR "Transfer Learning" OR "Learning, Transfer", "Deep Learning" OR "Learning, Deep" OR "Hierarchical Learning" OR "Learning, Hierarchical". Additionally, we examined the reference lists of included articles to identify any additional relevant studies not retrieved by the automatic searches. The whole search strategy [see Additional file 1].

### Inclusion and exclusion criteria

Eligibility criteria for inclusion were: (1) The study subjects included children and/or adolescents under 18 years; (2)The study subjects had asthma exacerbation/attack/deterioration and/or asthma exacerbation/attack/deterioration included in the primary or secondary outcome; (3) The language of the article was in English; (4) Research or application of ML for asthma exacerbation/attack/deterioration was conducted; (5) Observational studies (including retrospective, prospective, cohort studies, case-control studies, etc.) and randomized controlled trials (RCT) were eligible.

We excluded the following: (1) Books or dissertations or thesis or conference abstracts or comments or patents or awarded grant or editorial, or case reports; (2) Systematic reviews or Meta-analysis; (3) Non-full text articles.

### Screening and data extraction

Two authors (Chunni Zhou and Liu Shuai) independently scanned abstracts, titles, and citations retrieved by electronic and hand searches against the inclusion criteria to assess eligibility. Two review authors independently reviewed the full-text studies retrieved to determine final

**Table 1** Main characteristics of the identified studies reported in these studies

| First author, country, year | Study design | Data collection period | Population and Sample size | Definition of exacerbation/attack/deterioration | Outcome | ML | Validation methods | Result | Quality |
|---|---|---|---|---|---|---|---|---|---|
| Dexheimer JW, [10] America, 2007 | Retrospective observational study | Two months study period. | Children (aged 2–18 years) seen in the pediatric ED. 4,115 patient visits. | Not explained. | Freetext diagnosis of "asthma exacerbation," "status asthmaticus,""wheezing," or "reactive airway disease. | GP BN MMHC ANN SVM | Split-sample validation. | Expert BN AUC 0.959 (95% CI: 0.933–0.977), MMHC BN AUC 0.962 (95% CI: 0.935–0.980), ANN AUC 0.936 (95% CI: 0.902–0.961), and GP AUC 0.956 (95% CI: 0.923–0.976). | Moderate |
| Emeryk A, [31] Poland, 2023 | Prospective observational study | Six months study period. | 90 children (aged 0–17 years) diagnosed with asthma. | Not explained. | Asthma exacerbation level. | RF | 10-fold cross validation. | AUC values (younger children: 93.2% (95% CI, 92.1%-94.4%) and 93.0% (95% CI, 92.1%-93.9%), older children: 92.4% (95% CI, 90.9%-93.9%) and 92.4% (95% CI, 91.1%-93.7%)). | Moderate |
| Farion KJ, [12] Canada, 2013 | Prospective observational study | Phase 1 (from November 2006 to May 2007), phase 2 (from February 2009 to March 2010). | Children (aged 1–17 years) diagnosed with asthma. Phase 1: 240, Phase 2: 82. | Mild deterioration: brief treatment (less than 4 hours in the ED) and then discharged home; Moderate deterioration: longer, more aggressive treatment in the ED or observation room (4–16 hours total); Severe deterioration: maximum stabilization and hospitalization for ongoing treatment (more than 16 hours in the ED). | Patient's exacerbation severity. | NB DT EDT SVM IB1 IB10 | 10-fold cross validation. | Phase 1: NB: AUC 0.74(0.73, 0.76), DT: AUC 0.59(0.57, 0.62), EDT: AUC 0.70(0.68, 0.72), SVM: AUC 0.63(0.61, 0.65), IB1: AUC 0.56(0.54, 0.58) and IB10: AUC 0.68(0.66, 0.70). Phase 2: NB prediction accuracy 70.7%, PRAM accuracy 73.2% and physicians accuracy 78.0%. | Moderate |
| Gardeux V, [17] America, 2017 | Prospective cohort study | Three years study period. | 23 pediatric asthmatic patients (age not explained). | Not explained. | Asthma exacerbations. | RF NB DT SVM KNN | Holdout Validation. | Bayesian classifier achieved 74% accuracy (AUC 0.71; two-sided P ¼.039) | Moderate |
| Harmon I, [30] America, 2024 | Retrospective observational study | Four years study period from 2018 to 2021. | Children (aged 2–18 years). 991 patient encounters. | Not explained. | Asthma exacerbations. | Transformer MLP | unclear | Multi-layer perceptron-based model had the best performance ($F_1$ 0.95, specificity 1.00, sensitivity 0.91, negative predictive value 0.98, positive predictive value 1.00.). | Moderate |

**Table 1** (continued)

| First author, country, year | Study design | Data collection period | Population and Sample size | Definition of exacerbation/attack/deterioration | Outcome | ML | Validation methods | Result | Quality |
|---|---|---|---|---|---|---|---|---|---|
| Hurst JH, [26] America, 2022 | Retrospective observational study | Six years study period from January 1, 2014 to December 31, 2019. | 5982 children (aged 5–18 years) diagnosed with asthma. | Defined as any encounter with an asthma-related ICD9 or – 10 code and a prescription for a systemic steroid. | Asthma-related exacerbation. | LASSO<br>RF<br>XGBoost | Split-sample validation. | Three models performed moderately well (AUC 0.730–0.742) over all three time horizons. Decision rule (sensitivity 70%, positive predictive value 13.8% for 180 day, 2.9% for 30 day. | Moderate |
| Juhn YJ, [25] America, 2022 | Retrospective observational study | Two years study period from December 13, 2016, to December 12, 2018. | 246 children (aged < 18 years) had persistent asthma or met Predetermined Asthma Criteria (PAC). | Defined as an emergency department visit/hospitalization for asthma or an unscheduled visit for asthma requiring oral corticosteroids. | 1-year asthma exacerbation risk. | NB<br>GBM | Split-sample validation. | Asthmatic children with lower SES had greater BER (¼ 1.35 for HOUSES Q1 vs. Q2–Q4) and a higher proportion of missing information related to asthma care (41% vs. 24% for missing asthma severity). | Moderate |
| Kim D, [21] Korea, 2020 | Prospective observational study | One year study period from September 1, 2017 to August 31, 2018. | 14 children (aged 6–14 years) diagnosed with asthma. | Not explained. | PERF value. | K-means<br>MNL<br>LSTM | 10-fold cross validation. | On an average level, cluster 2 has a lower mean PEFR than cluster 1 (218.2 vs. 263.2), significant fluctuation of average PEFR values over the study period. | Moderate |
| Lee CH, [28] China, 2011 | Retrospective observational study | One years study period in 2015. | 33 children (age not explained) diagnosed with asthma. | Not explained. | Asthma attack. | DT<br>CAR | unclear | PBCAR accuracy 86.89% and recall 84.12%, PBDT accuracy 87.52% and recall 85.59. | Weak |
| Luo G, [14] America, 2015 | Prospective observational study | Two years study period. | 180 children (aged 2–18 years) diagnosed with asthma. | Not explained. | Asthma control deterioration. | RF<br>DS<br>NB<br>DNN<br>SVM<br>KNN | 10-fold cross validation. | Best model accuracy 71.8 %, sensitivity 73.8 %, specificity 71.4 %, and AUC 0.757. | Moderate |
| Okubo Y, [22] Japan, 2020 | Retrospective observational study | Seven years and nine months study period from July 1, 2010, to March 31, 2018. | 54,981 children (aged six months to 15 years) with asthma exacerbation. | Defined according to the International Classification of Diseases, Tenth Revision (ICD-10) codes. | Variation of antibiotic and adjunctive treatment. | HC | unclear | Proportions of antibiotic use decreased from 47.2% in 2010 to 26.9% in 2018. Utilization of antitussives, antihistamines, and methylxanthine showed decreasing trends, the use of mucolytics and ambroxol increased. | Moderate |

**Table 1** (continued)

| First author, country, year | Study design | Data collection period | Population and Sample size | Definition of exacerbation/attack/deterioration | Outcome | ML | Validation methods | Result | Quality |
|---|---|---|---|---|---|---|---|---|---|
| Overgaard SM, [29] America, 2022 | Retrospective observational study | Not explained. | Children (aged 6–17 years) diagnosed with active asthma (sample size not explained). | Defined as an inpatient/hospitalization visit for asthma diagnosis, or an ED visit for asthma diagnosis, or an outpatient visit of a patient with asthma diagnosis along with usage of oral corticosteroids medications. | Asthma exacerbations. | LR SVM RF NB MLP | 5-fold cross-validation. | LR model outperformed the other candidates producing a 0.8 AUC-ROC. | Weak |
| Patel SJ, [19] America, 2018 | Retrospective observational study | Four years study period from January 1, 2012, to December 31, 2015. | Children (aged 2–18 years) with asthma exacerbation. 29,392 ED visits. | Defined as concurrent treatment with salbutamol and systemic corticosteroids. | Hospitalization. | DT LR RF GBM | 3-fold cross validation. | DT AUC 0.72 (95% CI: 0.66–0.77), LR AUC 0.83 (95% CI: 0.82–0.83), RF AUC 0.82 (95% CI: 0.81–0.83), GBM AUC 0.84 (95% CI: 0.83–0.85). | Moderate |
| Rezaeiahari M, [27] America, 2024 | Retrospective cohort study | Two years study period. | 22,631 children (aged 5–18 years) (2,042 patients with asthma exacerbation, 20,589 patients without). | Defined as an ED visit and/or hospitalization. | ED visit, and/or hospitalization. | RF CRF | Bagging. | The model in the OOB sample AUC 72%, sensitivity 55% and specificity 78%, in the training samples AUC 73%, sensitivity 58% and specificity 77%. | Strong |
| Robroeks CM, [13] Netherlands, 2013 | Prospective longitudinal study | One year study period. | 39 children (aged 6–16 years) diagnosed with asthma. | Defined according to the latest ATS/ERS: 1) an increase in asthma symptoms (dyspnoea, cough and wheezing) and/or use of short acting b2-agonists for o2 days; and/or 2) a need for treatment with oral corticosteroids; and/or 3) a need for hospital admission. | Primary outcome: asthma exacerbation; Secondary outcome: asthma control score, Lung function tests. | SVM | 10-fold cross validation. | Six VOCs support vector machines (correct classification 96%, sensitivity 100%, specificity 93%). Seven VOCs models (correct classification 91%, sensitivity79%, specificity 100%) compared to patients without exacerbations. | Strong |
| Sanders DL, [9] America, 2006 | Prospective observational study | Two months study period. | Children (aged 2–18 years) diagnosed with asthma. 3,023 patient visits. | Free-text ED visit diagnosis of "asthma exacerbation", "status asthmaticus", "wheezing", or "reactive airway disease | Probability of asthma exacerbation in patients presenting to the ED. | BN | 3-fold cross validation. | AUC 0.959 (95% CI = 0.933–0.977). Sensitivity 90%, Specificity 88.3%, PPV 44.7%, NPV 98.8%, PLR 7.69 and NLR 0.11. | Weak |

**Table 1** (continued)

| First author, country, year | Study design | Data collection period | Population and Sample size | Definition of exacerbation/attack/deterioration | Outcome | ML | Validation methods | Result | Quality |
|---|---|---|---|---|---|---|---|---|---|
| Seol HY,[23] America, 2021 | Randomized controlled trial (RCT) | One year study period from December 13, 2016, to December12, 2017. | 184 children (aged < 18 years) diagnosed with asthma. | Defined as an emergency department visit/hospitalization for asthma or an unscheduled visit for asthma requiring oral corticosteroids. | Primary outcomes: 1-year asthma exacerbation risk; Secondary outcomes: time required for clinicians to review EHRs for asthma management. | NBC | unclear | AE frequency (IG 12% vs. CG 15%, OR: 0.82; 95%CI:0.374–1.96; *P*:0.626). Mean health care costs (IG -$1,036 [-$2177, $44] vs. CG +$80 [-$841, $1000]; P = 0.12). | Strong |
| Sills MR,[24] America, 2021 | Retrospective observational study | Five years study period from January 1, 2009, to December 31, 2013. | Children (aged 2–21 years) with asthma exacerbation. 9,069 ED visits. | Not explained. | Hospitalization. | RF<br>LR | Split-sample validation. | Auto ML AUCs 0.914 and 0.942, RF AUCs 0.831 and 0.886, LR AUCs 0.795 and 0.823. | Moderate |
| Spyroglou II,[20] Greece, 2018 | Retrospective observational study | Eight years study period from 2008 to 2016. | 65 children (aged 1–14.5 years) diagnosed with asthma. | Not explained. | Asthma exacerbations. | NB<br>TAN<br>SNBC | Repeated hold-out cross-validation. | Semi-naive network predicted exacerbation with an accuracy 93.84% and sensitivity 90.9%. | Moderate |
| Toti G,[16] America, 2016 | Case-Crossover Study | Eleven years study period from January 1, 2002, to December 31, 2012. | Pediatric asthmatic patients in pediatric emergency rooms (age and disease status not explained). 20,959 ED visits. | Not explained. | Patients went to the ER with an asthma attack. | ARM | Split-sample validation. | 27 rules were reported, with support ranging from 0.54% to 5.82% and FDR < 13%. | Moderate |
| Van Vliet D,[15] Netherlands, 2015 | Prospective longitudinal study | One year study period. | 96 children (aged 6–18 years) diagnosed with asthma. | Defined according to the latest ATS/ERS criteria and were classified as moderate or severe. | Asthma exacerbations. | KNN | Split-sample validation. | Model 1 AUC 0.47, Model 2 AUC 0.54 and Model 3 AUC 0.59. The K-nearest neighbor correctly predicted 52% of the exacerbations in the validation dataset. | Strong |

**Table 1** (continued)

| First author, country, year | Study design | Data collection period | Population and Sample size | Definition of exacerbation/attack/deterioration | Outcome | ML | Validation methods | Result | Quality |
|---|---|---|---|---|---|---|---|---|---|
| Van Vliet D,[18] Netherlands, 2017 | Prospective cohort study | One year study period. | 96 children (aged 6–18 years) diagnosed with asthma. | Defined according to the latest ATS/ERS criteria and were classified as moderate or severe. | Asthma exacerbations. | RF | Bagging. | First RF correct prediction was 82%, sensitivity 88%, specificity 75% and AUC 0.90. Second RF correct prediction was 65%, sensitivity 63% and specificity 67%. | Strong |
| Xu M,[11] America, 2011 | Retrospective observational study | Five to six years study period. | 581 children (aged 5–12 years) with mild-moderate asthma. | Defined as a visit to the emergency room or hospitalization for asthma symptoms during a clinical trial. | Severe asthma exacerbation. | RF | Holdout Validation. | Using 160–320 SNPs AUC 0.66, using 10 SNPs AUC 0.57 and using only clinical features AUC 0.54. | Moderate |

Note Abbreviations: ED, Emergency Department; AUC, Area Under the Curve; ROC, Receiver Operating Characteristic; ATS, American Thoracic Society; ERS, European Respiratory Society; GP, Gaussian process; BN, Bayesian Network; ANN, Artificial Neural Network; SVM, Support Vector Machine; 95%CI,95% Confidence Interval; MMHC, Max-Min Hill-Climbing; RF, Random Forest; NB, Naive Bayes model; DT, Decision Tree; EDT, Ensemble of Decision Tree; IB1 and IB10, Instance-based model with 1 and 10 nearest neighbors; PRAM, Pediatric Respiratory Assessment Measure; KNN, K- Nearest Neighbor; MLP, Multi-layer Perception; $F_1$, $F_1$ Score; ICD 9 or - 10, International Classification of Diseases 9 or - 10; XGBoost, eXtreme Gradient Boosting; LASSO, Least Absolute Shrinkage and Selection Operator; PAC, Predetermined Asthma Criteria; GBM, Gradient boosting machine; SES, SocioEconomic Status; BER, Balanced Error Rate; HOUSES, HOUsing-based SocioEconomic Status; PEFR, Peak Expiratory Flow Rate; MNL, Multinomial logistic; LSTM, Long Short-Term Memory; CAR, Class-Association Rule; PBCAR, Pattern Based Class-Association Rule; PBDT, Pattern Based Decision Tree; DS, Decision stumps; DNN, Deep Neural Network; HC, Hierarchical Clustering; LR, Logistic regressions; CART, Classification And Regression Tree; OOB, Out of Band; VOCs, Volatile Organic Compounds; PPV, Positive Predictive Value; NPV, Negative Predictive Value; PLR, Positive Likelihood Ratio; NLR, Negative Likelihood Ratio; EHRs, Electronic Health Records; NBC, Naive Bayes Classifier; AE, Asthma Exacerbation; IG, Intervention Group; CG, Control Group; OR, Odds Ratio; TAN, Tree-augmented Naive Bayes; SNBC, Semi-Naive Bayes classifiers; ER, Emergency Room; ARM, Association Rule Mining; FDR, False Discovery Rate; SNPs, Single Nucleotide Polymorphisms

eligibility. Disagreements were discussed and resolved by consensus, and if necessary, a third author (Meng Li) was involved.

Data were extracted by one reviewer (Chunni Zhou) and checked for consistency by the other two reviewers (Liu Shuai and Meng Li). Data extracted included first author, country, year, study design, data collection period, study population, sample size, type of ML algorithm, definition of asthma exacerbation/attack/deterioration, outcome events, and study results. For the ML algorithms, we also extracted validation methods and performance metrics. In addition, we read through each study to generalize and categorize the research objectives. Due to significant methodological heterogeneity among the studies, a meta-analysis was not conducted. Instead, a narrative synthesis of the results was performed, and complete details of the included studies are reported in Table 1.

### Quality assessment

The Effective Public Health Practice Project (EPHPP) quality assessment tool for quantitative studies [37] was used to assess each research regarding potential biases and global study quality. Studies were given a global rating of strong, moderate, or weak based on the score. The tool was used for removing confounders, blinding, intervention integrity, and analysis, as these were irrelevant to the study designs assessed in this review. This left the following areas: selection bias, study design, data collection methods, and withdrawals and dropouts. One author (Chunni Zhou) conducted this assessment, and a discussion was undertaken with the second author.

## Results

### Study selection

Figure 1 shows the study selection process. A total of 675 papers were identified from four databases (PubMed (136), Elsevier (47), Web of Science (333), and Ebsco (159)). After excluding 335 duplicates, 340 papers were screened by titles and abstracts, leading to 31 potentially eligible papers. Then, full-text screening of these articles confirmed eligibility for 16. Additionally, examining the references of these articles yielded 7 more, totaling 23 articles included in the review (Fig. 1).

### Study characteristics

The publication year of these papers they were ranged from 2006 to 2024. Eight studies were published between 2006 and 2015 [9–15, 28] and 15 between 2016 and 2024 [16–27, 29–31]. Among these studies, 14 studies were from America [9–11, 14, 16, 17, 19, 23–27, 29, 30], three were from the Netherlands [13, 15, 18], and one each was from Canada [12], Greece [20], Korea [21], Japan [22], China [28] and Poland [31] (Fig. 2).

Nine were prospective studies [9, 12–15, 17, 18, 21, 31], including two prospective cohort studies [17, 18] and two prospective longitudinal studies [13, 15], with follow-up times of one [13, 15, 18], and three years [17]. Thirteen were retrospective studies [10, 11, 16, 19, 20, 22, 24–30], including one retrospective cohort study [27] and one case-crossover study [16], with follow-up periods of two [27] and eleven years [16]. One study was a randomized controlled trial with a 1-year follow-up [23]. In the randomized controlled trial, the intervention positively affected exacerbation outcomes [23] (Fig. 2).

The age range for populations varied across the studies: five included children aged 2–18 years [9, 10, 14, 19, 30], three included children aged 0–17 years [23, 25, 31], two included children aged 5–18 years [26, 27], two included children aged 6–18 years [15, 18], one each included children aged six months to 15 years [22], 1–14.5 years [20], 1–17 years [12], 2–21 years [24], 5–12 years [11], 6–14 years [21], 6–16 years [13] and 6–17 years[29] and three did not specify the age of the pediatric participants [16, 17, 28] (Fig. 2).

The sample size varied from 14 to 54981 (eight studies ≤ 100 [13, 15, 17, 18, 20, 21, 28, 31], six studies ≤ 1,000 [11, 12, 14, 23, 25, 30], four studies ≤ 10,000 [9, 10, 24, 26], four studies > 10,000 [16, 19, 22, 27] and one study not explained [29]). Full details of the included studies are reported in Table 1 (Fig. 2).

### Definition of exacerbation and outcome

Ten studies did not specify a definition of asthma exacerbation [10, 14, 16, 17, 20, 21, 24, 28–31], three studies defined asthma exacerbation according to the most recent ATS/ERS [13, 15, 18], three studies defined asthma exacerbation using emergency room visits and hospitalizations [11, 12, 27], two studies defined asthma exacerbation using emergency room visits/hospitalizations or oral corticosteroid [23, 25], two studies defined asthma exacerbation using International Classification of Diseases codes ICD9 or – 10 [22, 26], one study defined asthma exacerbation using concomitant receipt of albuterol and systemic corticosteroids [19], one study defined asthma exacerbation using only emergency room visits [9] and one study defined asthma exacerbation using emergency room visits or hospitalizations or outpatient visit with usage of oral corticosteroids medications [29]. Seventeen of the studies had a primary or secondary outcome of pediatric asthma exacerbation [9–13, 15–18, 20, 23, 25, 26, 28–31], while the remaining six studies included populations with pediatric asthma exacerbations [14, 19, 21, 22, 24, 27]. Therefore, the outcomes of the studies were mainly related to emergency room visits or hospitalizations [19, 24, 27], peak expiratory flow rate (PEFR) values [21], asthma control exacerbation [14], and antibiotic variants and adjunctive therapy [22].

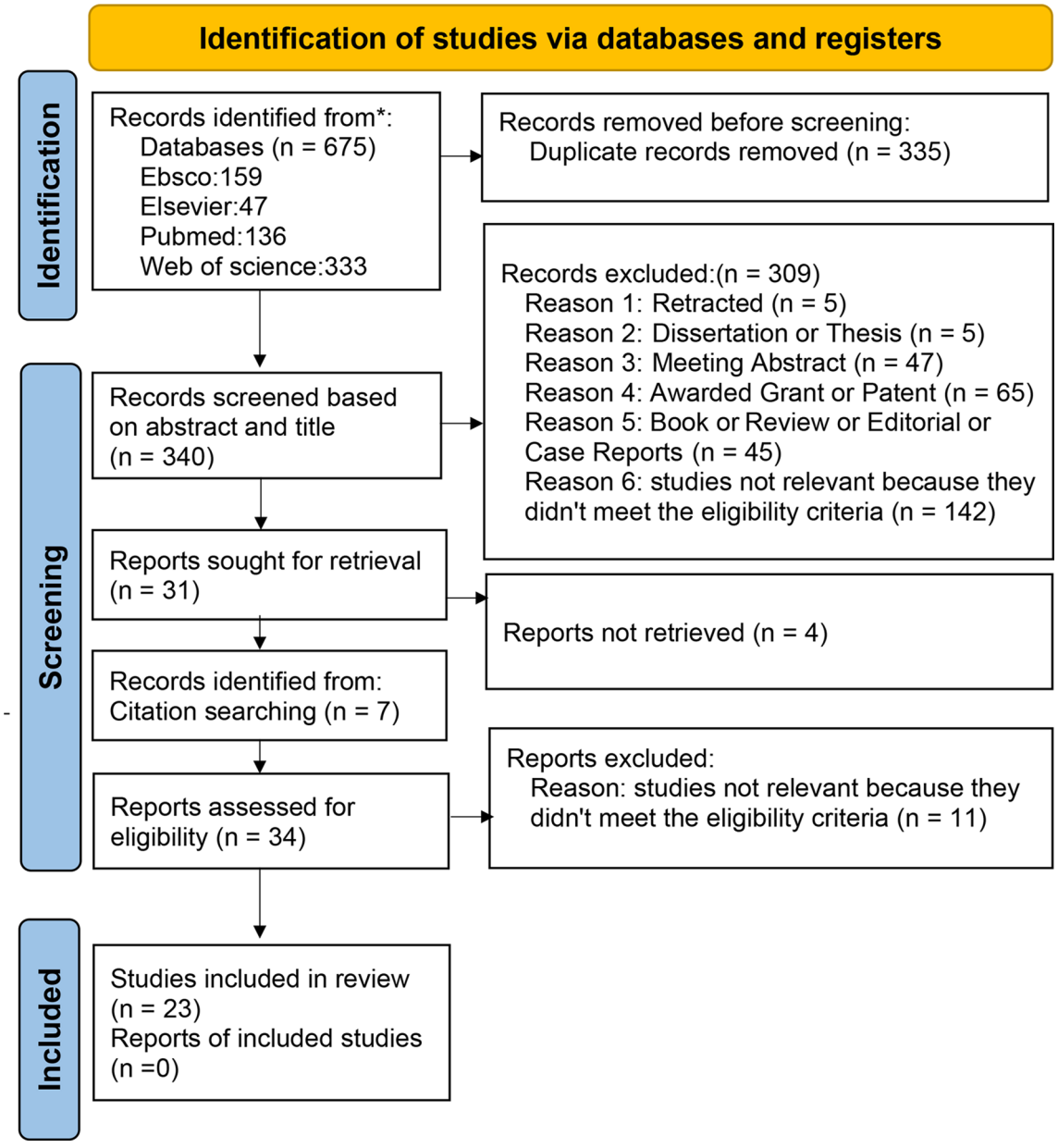


**Fig. 1** Preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram

**ML model related characteristics**

Regarding learning algorithms, 23 studies utilized 59 different ML algorithms, which were categorized with the most popular being Bayesian Networks (BN), followed by Random Forests (RF), Decision Trees (DT), Neural Networks (NN) and Support Vector Machines (SVM) (Fig.3).

Because of data limitations, only five studies were included in this study to research the performance of their ML models, and the performance metrics were accuracy, sensitivity, specificity, Area Under the Curve (AUC), Positive Predictive Value (PPV) and Negative Predictive Value (NPV). Overall, most of the values of the six metrics of all the models in the five studies were high, especially the specificity, AUC and NPV were close to 100% for some models, and among all the metrics, the distribution of accuracy was the most concentrated, with most models around 70%, and the remaining metrics have a more dispersed distribution of values. The five models of Dexheimer JW et al [10] have higher values of sensitivity, specificity, AUC and NPV, among which the NPV of BN, Max-Min Hill-Climbing (MMHC) and Gaussian process (GP) reaches 98.9%, but the PPV of the five models are low, especially Artificial Neural Network (ANN), which has a PPV of only 38%. The values of the five models of Gardeux V et al [17] for the six metrics are relatively close to each other, with values between 60%

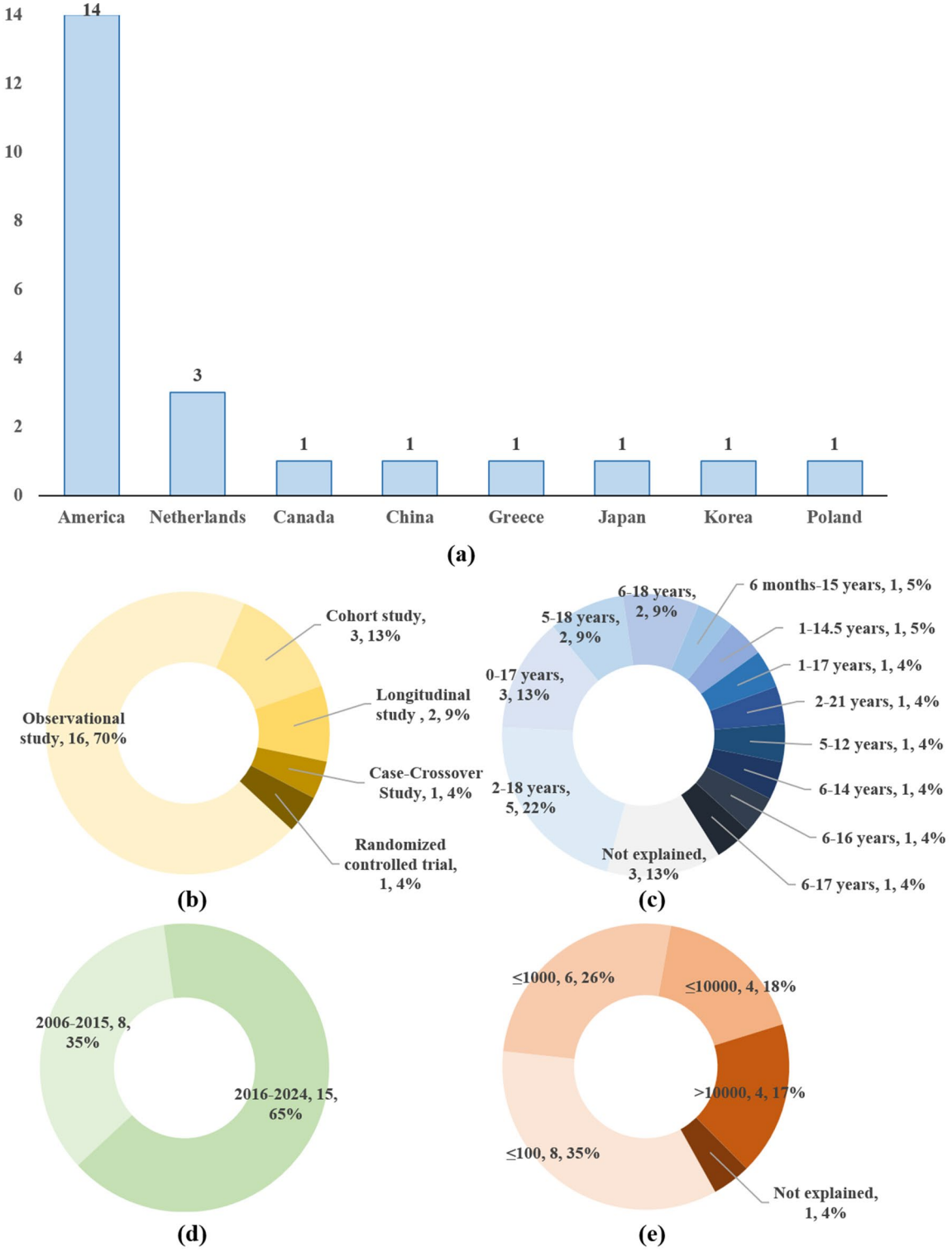


**Fig. 2** Study characteristics of the included studies. *Note* (**a**) study setting of the included studies; (**b**) study design of the included studies; (**c**) study population of the included studies; (**d**) publication years of the included studies; (**e**) sample size of the included studies

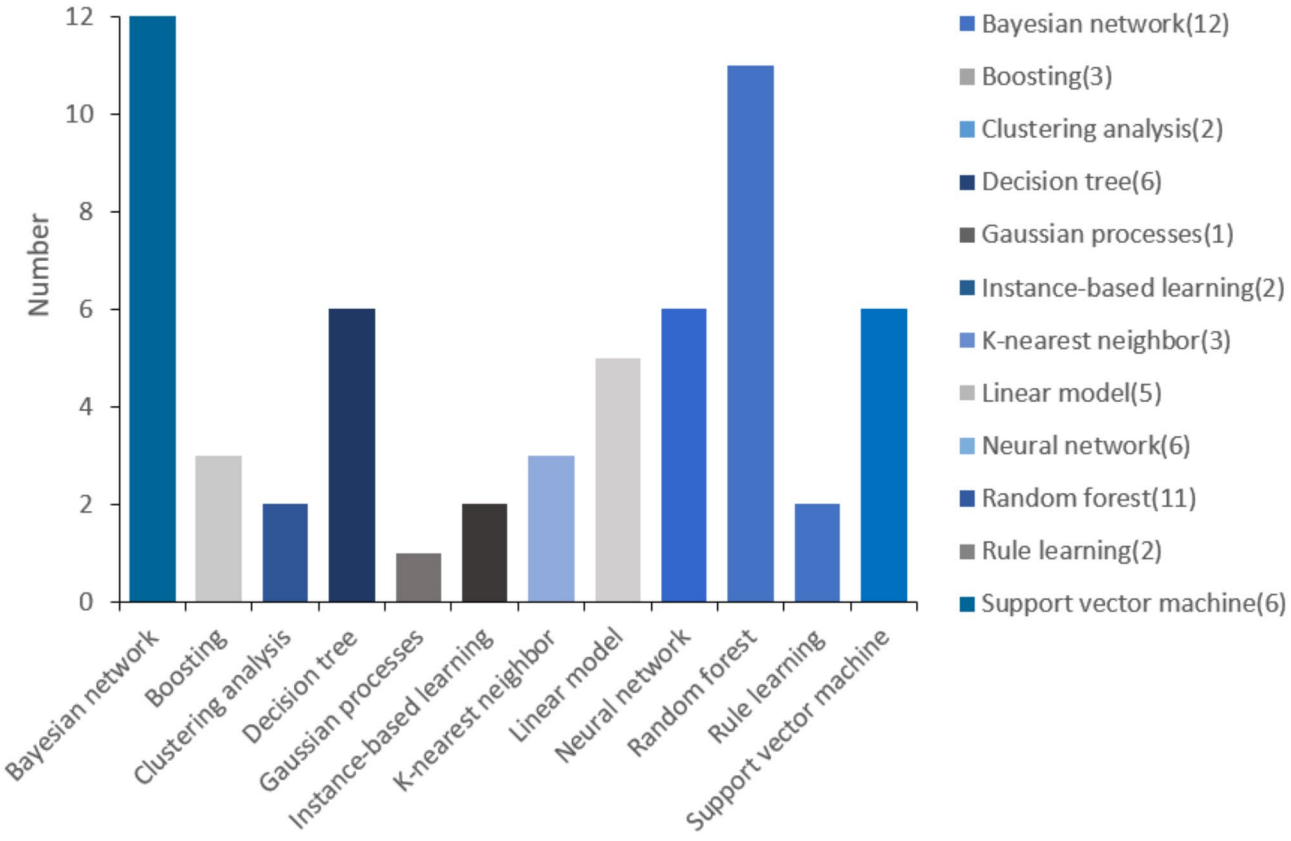


**Fig. 3** Histogram of different ML algorithms for asthma exacerbation management. *Note*: There were a total of 59 models across the 23 studies, which were categorized to give a total of 12 categories of models

and 70%. The accuracy, specificity, AUC and NPV of the six models of Luo G et al [14] were around 70% and 80%, but the sensitivity and PPV values were lower, with RF having the lowest sensitivity of 38.3%, showing a rectangular pattern (Fig. 4).

Farion KJ et al [12] and Sanders DL et al [9] each included only one model. In the NB model of Farion KJ et al [12], the highest value of the five reported metrics was 85% (PPV), while the lowest value was 53% (NPV). In contrast, the Bayesian network model of Sanders DL et al [9] reported the highest value as 98.8%(NPV) and the lowest value as 44.7% (PPV).

Regarding algorithm validation methods, nine studies used cross-validation [9, 12–14, 19–21, 29, 31], six studies used split-sample validation [10, 15, 16, 24–26], two studies used bagging validation [18, 27], two studies used holdout validation [11, 17], and four studies did not mention validation methods [22, 23, 28, 30].

Of the 23 studies included, 21 studies dealt with classification tasks using ML models [9–15, 17–21, 23–31], only one study dealt with clustering tasks [22], and one study dealt with association analysis tasks using association rule mining [16].

The study showed that the number of variables entered into the model varied across studies, with 5 studies having a variable count of ≤ 10 variables [9, 18, 21, 22, 27], 13 studies having a variable count of ≤ 50 variables [10, 12, 14–17, 19, 20, 23–25, 28, 29], 1 study having a variable count of > 100 variables [13], and 4 studies having an unknown specific variable count [11, 26, 30, 31]. In the 23 studies, the types of variables input into the model were a mixture of numerical and categorical variables [9–31]. The numerical variables mainly included physiological indicators of patients (such as BMI, and pulmonary function indicators), environmental data, and genetic data. The categorical variables mainly included basic patient characteristics (such as gender, age, and ethnicity), clinical characteristics (such as allergic constitution, comorbid conditions, and asthma severity), treatment-related factors (such as medication use and treatment group), and other clinical diagnostic information (such as symptom severity).

In addition, regarding Explainable Artificial Intelligence (XAI), five studies were found to use feature importance maps to improve the interpretability of model results [11, 18, 19, 24, 27], five studies to use interpretable models and visualize model structures and processes [9, 10, 16, 20, 28] and one study to use the SHapley Additive explanation (SHAP) method to calculate shapley values [30].

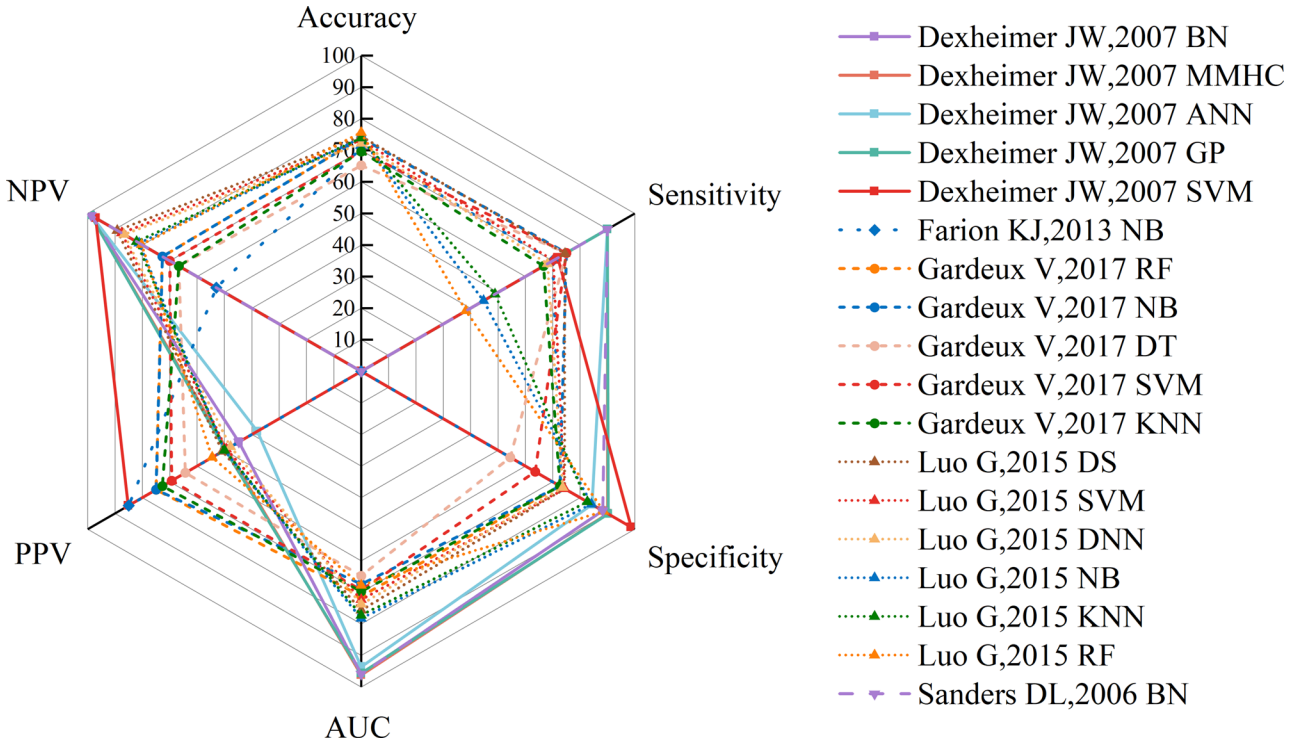


**Fig. 4** Radar charts of ML model performance metrics. Note: Because of data limitations, all five models studied by Dexheimer JW were missing accuracy, with the SVM also missing AUC; the NB model studied by Farion KJ was missing AUC; and the BN model studied by Sanders DL was missing accuracy. BN, Bayesian Network; MMHC, Max-Min Hill-Climbing; ANN, Artificial Neural Network; GP, Gaussian process; SVM, Support Vector Machine; NB, Naive Bayes model; RF, Random Forest; DT, Decision Tree; KNN, K- Nearest Neighbor; DS, Decision stumps; DNN, Deep Neural Network

## Applications of ML algorithms in pediatric asthma exacerbations (categorized by disease management)

### *Assessment of risk factors*

Eight studies have utilized ML to assess risk factors for pediatric asthma exacerbations, exploring genomic data, environmental elements, and socioeconomic status [11, 16, 17, 21, 25–28]. Two studies focus on genomics [11, 17], two on social factors [25, 27] and three on environmental factors such as indoor and outdoor air pollutants [16, 21, 26, 28]. Some studies have analyzed the effects of genetic polymorphisms and air pollutants on pediatric asthma exacerbations using Random Forest classifiers and association rule mining techniques [11, 16, 28], and one of them proposed two novel data mining methods (pattern-based decision tree (PBDT) and pattern-based class association rule (PBCAR)) to combine patient biosignals and environmental data for the application of asthma exacerbation. others have used deep learning algorithms, such as Long Short-Term Memory (LSTM) modeling, to predict the risk of pediatric asthma exacerbations and assessed the effects of indoor particulate matter concentrations on PEFRs in pediatric asthma [21]. In addition, studies also evaluated the performance of ML models across different socioeconomic groups, aiming to minimize biases [25, 27]. Together, these studies emphasize the importance of individual differences and environmental factors in the management of pediatric asthma exacerbations.

### *Diagnosis and prediction of pediatric asthma exacerbations*

Nine studies have applied ML to diagnose pediatric asthma exacerbations with high accuracy, leveraging clinical data and patient characteristics [9, 10, 12, 13, 15, 18, 20, 30, 31]. Three studies developed and evaluated Bayesian networks for diagnosing patients in line with treatment guidelines in pediatric emergency departments and predicting exacerbations post-medication withdrawal [9, 10, 20]. Three other studies utilized Volatile Organic Compounds (VOCs) and inflammatory markers to diagnose and predict exacerbations, with one noting high accuracy for certain VOC combinations [13, 15, 18]. One study used this to accurately identify pediatric asthma exacerbations from prehospital records by modifying an existing rule-based computable phenotype (CP) and creating a new machine learning-based CP [30]. One study used an AI-assisted home stethoscope and found that the parameters provided by the device were very effective in detecting pediatric asthma exacerbations [31]. Still another study compared the efficacy of various algorithms, including Bayesian networks, ANNs, SVMs, and Gaussian processes, in predicting asthma exacerbations

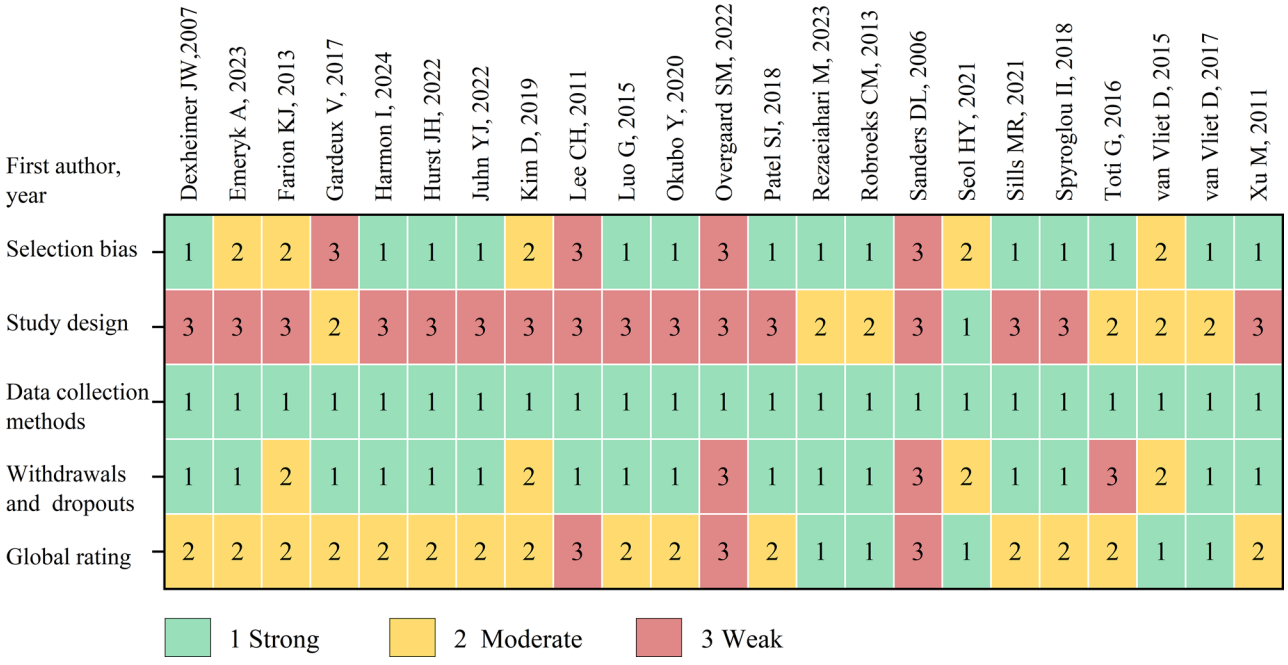


**Fig. 5** Quality assessment. *Note* The confounders, blinding, intervention integrity, and analyses did not apply to any of the studies and were therefore removed

in the ED, concluding that all achieved high accuracy [12].

#### *Optimization and allocation of medical resources*

Three studies explored the use of ML for optimizing medical resource allocation in pediatric asthma exacerbations [19, 22, 24]. One study compared four ML models, combining clinical, environmental, and social data to predict demand for hospitalization, with gradient boosting performing the best results [19]. Another applied automated machine learning algorithms (autoML), which outperforming traditional ML [24]. The third analyzed hospitalization patterns in Japan, founding that antibiotic use and the use of other adjunctive treatments differed significantly between hospitals [22].

#### *Comprehensive asthma management*

Three studies have applied ML to comprehensive pediatric asthma exacerbations management [14, 23, 29]. One study combined ML algorithms to predict asthma control exacerbations one week in advance by analyzing clinical and environmental data [14]. Two studies evaluated an artificial intelligence-assisted clinical decision support system (AI-CDS) [23, 29], specifically the Asthma Guidance and Prediction System (A-GPS), which uses EHRs to provide clinical information and predict the risk of asthma exacerbation [23]. While all three studies utilized ML to enhance asthma management, the former study emphasized model development and improvement of prediction ability [14] and the latter two assessed AI-CDS in clinical practice [23, 29].

### Quality assessment

The EPHPP quality assessment in Fig. 5 rated 5 studies as strong [13, 15, 18, 23, 27], 15 as moderate [10–12, 14, 16, 17, 19–22, 24–26, 30, 31] and 3 as weak [9, 28, 29].

## Discussion

This systematic review covers a broader and more recent time frame, spanning from Jan 2000 to Jan 2025, providing insights into the evolving use of ML in pediatric asthma exacerbations. It contains more than just predictions [4, 36, 38, 39], covering risk factor assessment, diagnosis and prediction of pediatric asthma exacerbations, optimization and allocation of medical resources, and comprehensive asthma management, offering a more holistic understanding of ML's role in this domain.

### Findings

The review also highlights that majority of ML applications in the included studies were predictive models for pediatric asthma exacerbations. This trend likely reflects the rapid onset and dynamic nature of asthma exacerbation, which can be life-threatening. Prediction of pediatric asthma exacerbations plays a crucial role in enabling preventive interventions and targeted treatment [40]. Furthermore, disease diagnosis can provide physicians with actionable predictive data to support decision-making, enhance healthcare process efficiency, and reduce

costs [40–42]. ML algorithms have been applied not only in predicting acute exacerbations of chronic obstructive pulmonary disease (COPD) [43–45] and acute kidney injury [46, 47], but also in detecting and diagnosing conditions such as asthma, heart disease, and diabetes [48–50]. Additionally, ML aids in creating personalized treatment plans for diseases like cancer and rheumatoid arthritis [51, 52], while optimizing healthcare resources management [53, 54].

Because of the broad definition of pediatric asthma exacerbation, this study included studies that explicitly stated the keyword "asthma exacerbation". This review also found that the definitions of pediatric asthma exacerbations varied across studies, with most studies defining pediatric asthma exacerbations as hospitalization, emergency visits, and specific medical interventions, and the differing definitions of exacerbations lead to non-comparable findings. In addition, different definitions may have an impact on the diagnosis of pediatric asthma exacerbations, with looser definitions potentially including more potential pediatric asthma exacerbations, thus increasing sensitivity, but also diagnosing asthma exacerbations in patients who do not have an asthma exacerbation, which reduces specificity and leads to more false-positive diagnoses; therefore standardizing the definition of pediatric asthma exacerbation could help improve both the quality of the study and the accuracy of the diagnosis [55, 56].

ML research in pediatric asthma is also different from adult asthma. The pathogenesis of pediatric asthma is relatively complex, and many risk factors are still unknown; therefore, in studies of pediatric asthma, the focus is usually on factors associated with child growth and development, such as family history and genetic predisposition [11, 17, 32]. Still, these factors are often difficult to control, and these factors may be less significant in studies of adult asthma exacerbations, which have focused more on lifestyle and environmental factors, such as air pollution and occupational exposures [57, 58]. Thus, in pediatric asthma, controlling certain environmental factors, such as tobacco smoke exposure, pet hair and dust mites, may reduce the risk of asthma exacerbation [26, 32, 59]. In addition, ML models for pediatric asthma focus more on the explanatory nature of the models so that they can be accepted and used by physicians and parents. The interpretability of black-box models (such as the more complex ML and DL models) can be improved using techniques like feature importance analysis and Local Interpretable Model-agnostic Explanations (LIME), which are post-hoc interpretation methods [60, 61]. Alternatively, one can directly use interpretable models, such as linear models and decision trees, which have simple structures and are easy to understand and interpret. In addition, textual interpretation and visualization of models or results can improve the interpretability of models and results to some extent. There is no unified and objective standard for assessing interpretability, and different methods and application scenarios may require different assessment indicators [62]. In addition, approaches integrating multiple ML algorithms have shown promising results in pediatric asthma exacerbation studies, especially when considering multiple meteorological, environmental, and pollen factors [26]. This suggests that combining different machine-learning algorithms may provide more accurate models for pediatric asthma exacerbation studies [12, 14, 17, 21]. Meanwhile, the emerging development of deep learning models has also shown advantages as they can efficiently process and refine the complex nonlinear relationships between risk factors, thus improving the model accuracy [14, 21, 63].

The inclusion of this systematic review revealed that the number of variables entered into the model varied across studies. Upon comparison, it was found that studies with a smaller number of model inputs included a correspondingly smaller number of study subjects, used fewer types of ML algorithms, and had simple models that were easy to manipulate, with high model interpretability, and that the ML in these types of studies was more focused on the application of clinical practice for pediatric asthma exacerbation; whereas, studies with a larger number of model inputs included a very large number of study subjects, and also used multiple ML algorithms for comparison, however crosswise, the accuracy of the resulting models was also higher, and the study focused more on ML method and prediction performance.

When assessing model performance, using a combination of metrics is essential, as relying on a single metric can be misleading. Different metrics capture different aspects of model performance, providing a more comprehensive evaluation. For instance, using accuracy alone can be very deceptive, particularly with unbalanced dataset. In such cases, accuracy may overestimate model effectiveness by favoring the majority class while masking poor performance on minority classes. While AUC (area under the ROC curve) is robust to class imbalanced and offers a holistic view of model performance, it also has limitations. AUC does not convey how well the model performs at particular decision thresholds, which is critical for practical applications. For example, in pediatric asthma exacerbation studies, the performance of the model under specific decision thresholds can directly affect clinical outcomes. Therefore, it is necessary to refer to metrics such as sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV). For example, if the model is used for screening and diagnosis of pediatric asthma exacerbations, then high sensitivity and NPV are essential to reduce underdiagnosis and underreporting, while high specificity and PPV help to minimize misdiagnosis and misreporting [40, 64–66].

To effectively evaluate model performance, the choice of metrics should align with the characteristics of the dataset and the objectives of the modeling task. AUC is widely used to comprehensively assess a model's ability to distinguish between categories. It summarizes the model's performance under different thresholds and is particularly useful for unbalanced datasets. Sensitivity and specificity are critical when evaluating the performance of a model on positive and negative classes. For situations where false positives and false negatives need to be balanced, metrics such as precision and recall (sensitivity) can be combined into an F1 score to provide a balanced assessment, especially in unbalanced datasets. In addition, accuracy is a straightforward metric for measuring the proportion of correct predictions. However, in unbalanced datasets, accuracy can be misleading, and metrics such as Precision-Recall Curve and Area Under Precision-Recall Curve (AUPRC) provide a more accurate picture of model performance.

Ultimately, the selection of evaluation metrics should be tailored to the specific goals of the modeling task. For instance, AUC measures overall discriminatory power, sensitivity and specificity assess category-specific performance, and theF1 scores balances precision and recall, providing a comprehensive understanding of model effectiveness [67–69].

### Implications and recommendations

Regarding the diagnosis of pediatric asthma exacerbation, the Global Strategy for Asthma Management and Prevention (Updated 2024) can be referred to for a comprehensive diagnosis by combining information from various aspects such as clinical symptoms, medical history, physical examination, and pulmonary function tests. Accurate diagnosis helps to detect signs of asthma exacerbation and take targeted treatment measures. However, it varies from region to region and should be standardized according to local diagnostic criteria [3, 70].

In the clinical use of ML models to assist decision-making, with the help of explanatory tools such as LIME, SHAP, the results of the model can be interpreted to help doctors and parents understand the model's decisions. For example, through the SHAP method one can clarify which risk factors have a greater impact on the current prediction results, so as to take more targeted preventive measures, but also can choose some of its own ML algorithms with better interpretability, such as decision trees, logistic regression and so on [60–62].

When evaluating the performance of the model, in addition to focusing on metrics such as accuracy and AUC, attention should also be paid to metrics such as the sensitivity, specificity, PPV and NPV of the model. These metrics can more comprehensively reflect the performance of the model in practical applications and help doctors and assess the reliability and usefulness of the model [64–66, 69].

### Strengths and limitations of the study

The strengths of this systemic review lie in its comprehensive search strategy, adherence to a rigorous systematic review methodology and reporting guidelines, and the independent assessment by researchers during title, abstract, and full-text screening, with data extraction verified by multiple reviewers. However, this review has some limitations. First, non-English studies were excluded, which may limit the generalizability of findings. Second, the definition of asthma exacerbation was not standardized across studies, making comparisons difficult. Third, meta-analysis could not be conducted due to significant heterogeneity in study samples, participants, and outcomes.

### Future research

Future research on ML in pediatric asthma exacerbations holds considerable promise. Enhancing data quality and diversity is crucial, with the inclusion of broader datasets encompassing pediatric asthma genetic information, environmental factors, and lifestyle habits. Additionally, algorithmic advancements, especially in deep learning, will drive further personalization of treatment, leading to improved efficacy. The integration of real-time monitoring systems using wearables and smart devices will support detection and prevention. Finally, interdisciplinary collaboration among experts in medicine, data science, and engineering will be essential in addressing complex problems and developing more effective asthma management tools.

## Conclusions

The systematic review indicates great potential for ML in pediatric asthma exacerbation management, including risk identification, diagnosis, and personalized care. However, challenges such as data quality, algorithm optimization, and interdisciplinary collaboration need to be addressed in clinical practice. Future work should prioritize model robustness, data security, and clinical testing to advance the field.

#### Abbreviations

| | |
|---|---|
| ED | Emergency Department |
| HRQL | Health-Related Quality of Life |
| ML | Machine Learning |
| EHRs | Electronic Health Records |
| RCT | Randomized Controlled Trials |
| EPHPP | Effective Public Health Practice Project |
| ERS | European Respiratory Society |
| ATS | American Thoracic Society |
| PEFR | Peak Expiratory Flow Rate |
| BN | Bayesian Network |
| RF | Random Forest |
| DT | Decision Tree |

| | |
|---|---|
| NN | Neural Network |
| SVM | Support Vector Machine |
| AUC | Area Under the Curve |
| PPV | Positive Predictive Value |
| NPV | Negative Predictive Value |
| MMHC | Max-Min Hill-Climbing |
| GP | Gaussian process |
| ANN | Artificial Neural Network |
| XAI | Explainable Artificial Intelligence |
| SHAP | SHapley Additive explanation |
| LSTM | Long Short-Term Memory |
| VOCs | Volatile Organic Compounds |
| CP | Computable Phenotype |
| auto ML | Automated Machine Learning |
| PBDT | Pattern Based Decision Tree |
| PBCAR | Pattern Based Class-Association Rule |
| AI-CDS | Artificial Intelligence-assisted Clinical Decision Support |
| A-GPS | Asthma Guidance and Prediction System |
| COPD | Chronic Obstructive Pulmonary Disease |
| LIME | Local Interpretable Model-Agnostic Explanations |
| ICD | International Classification of Diseases |
| AUPRC | Area Under Precision-Recall Curve |

## Supplementary information

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Supplementary Material 1

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**Author contributions**
M. L. conceived this article. C. Z. and L. S. searched and selected literature, extracted data and assessed the quality of the included studies. C. Z. wrote the original manuscript. M. L. reviewed and amended the original manuscript. All authors contributed to and have approved the final manuscript.

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**Data availability**
No datasets were generated or analysed during the current study.

## Declarations

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Clinical trial number**
Not applicable.

**Competing interest**
The authors declare no competing interests.

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**References**

1. Alharbi ET, Nadeem F, Cherif A.Predictive models for personalized asthma attacks based on patient's biosignals and environmental factors: a systematic review. BMC Med Inform Decis Mak. 2021;21(1):345.
2. Horne EMF, McLean S, Alsallakh MA, Davies GA, Price BD, Sheikh, et al. Defining clinical subtypes of adult asthma using electronic health records: analysis of a large UK primary care database with external validation. Int J Med Inform. 2023;170:104942.
3. Global Initiative for Asthma. Global Strategy for Asthma Management and Prevention, 2024. May 2024. Available from: www.ginasthma.org.
4. Rodríguez-Martínez CE, Sossa-Briceño MP, Forno E.Composite predictive models for asthma exacerbations or asthma deterioration in pediatric asthmatic patients: a systematic review of the literature. Pediatr Pulmonol. 2023;58(10):2703–18.
5. Dexheimer JW, Abramo TJ, Arnold DH, Johnson K, Shyr Y, Ye F, et al. Implementation and evaluation of an integrated computerized asthma management system in a pediatric emergency department: a randomized clinical trial. Int J Med Inform 2014;83:805–13.
6. Centers for Disease Control and Prevention, National Center for Environmental Health, Asthma Attacks among People with Current Asthma, 2014–2017. 2019. Available from: https://www.cdc.gov/asthma/asthma_stats/attacks-current-asthma.htm#:%7E:text=In%20an%20asthma%20attack%2C%20the%20airways%20become%20inflamed%2C,The%20percentage%20of%20asthma%20attacks%20varied%20by%20state. 22 Jun 2024.
7. QuickStats: percentage of All Emergency Department (ED) Visits Made by Patients with Asthma, by Sex and Age Group - National Hospital Ambulatory Medical Care Survey, United States 2014-2015. MMWR Morb Mortal Wkly Rep. 2018, 67 (5), 167.
8. Dexheimer JW, Abramo TJ, Arnold DH, Johnson KB, Shyr Y, Ye F, et al. An asthma management system in a pediatric emergency department. Int J Med Inform 2013;82:230–38.
9. Sanders DL, Aronsky D. Detecting asthma exacerbations in a pediatric emergency department using a Bayesian network. AMIA Annu Symp Proc. 2006;684–88.
10. Dexheimer JW, Brown LE, Leegon J, Aronsky D.Comparing decision support methodologies for identifying asthma exacerbations. Stud Health Technol Inform. 2007;129(2):880–84.
11. Xu M, Tantisira KG, Wu A, Litonjua AA, Chu JH, Himes BE, et al. Genome Wide Association Study to predict severe asthma exacerbations in children using random forests classifiers. BMC Med Genet. 2011;12:90.
12. Farion KJ, Wilk S, Michalowski W, O'Sullivan D, Sayyad-Shirabad J.Comparing predictions made by a prediction model, clinical score, and physicians. Appl Clin Inform. 2013;4(3):376–91.
13. Robroeks CM, Van Berkel JJ, Jöbsis Q, Van Schooten FJ, Dallinga JW, Wouters EF, et al. Exhaled volatile organic compounds predict exacerbations of childhood asthma in a 1-year prospective study. Eur Respir J 2013;42:98–106.
14. Luo G, Stone BL, Fassl B, Maloney CG, Gesteland PH, Yerram SR, et al. Predicting asthma control deterioration in children. BMC Med Inform Decis Mak. 2015;15:84.
15. Van Vliet D, Alonso A, Rijkers G, Heynens J, Rosias P, Muris J, et al. Prediction of asthma exacerbations in children by innovative exhaled inflammatory markers: results of a longitudinal study. PLoS One. 2015;10(3).
16. Toti G, Vilalta R, Lindner P, Lefer B, Macias C, Price D. Analysis of correlation between pediatric asthma exacerbation and exposure to pollutant mixtures with association rule mining. Artif Intell Med. 2016;74:44–52.
17. Gardeux V, Berghout J, Achour I, Schissler AG, Li Q, Kenost C, et al. A genome-by-environment interaction classifier for precision medicine: personal transcriptome response to rhinovirus identifies children prone to asthma exacerbations. J Am Med Inform Assoc 2017;24:1116–26.
18. Van Vliet D, Smolinska A, Jöbsis Q, Rosias P, Muris J, Dallinga J, et al. Can exhaled volatile organic compounds predict asthma exacerbations in children? J Breath Res 2017;11:01601.
19. Patel SJ, Chamberlain DB, Chamberlain JM.A machine learning approach to predicting need for hospitalization for pediatric asthma exacerbation at the time of emergency department triage. Acad Emerg Med. 2018;25(12):1463–70.
20. Spyroglou Il SG, Rigas AG, Paraskakis EN.Evaluation of Bayesian classifiers in asthma exacerbation prediction after medication discontinuation. BMC Res Notes. 2018;11(1):522.
21. Kim D, Cho S, Tamil L, Song DJ, Seo S. Predicting asthma attacks: effects of indoor PM concentrations on peak expiratory flow rates of asthmatic children. IEEE Access. 2019;8:8791–97.
22. Okubo Y, Horimukai K, Michihata N, Morita K, Matsui H, Fushimi K, et al. Recent practice patterns and variations in children hospitalized for asthma exacerbation in Japan. Int Arch Allergy Immunol 2020;181:926–33.

23. Seol HY, Shrestha P, Muth JF, Wi CI, Sohn S, Ryu E, et al. Artificial intelligence-assisted clinical decision support for childhood asthma management: a randomized clinical trial. PLoS One. 2021;16(8).
24. Sills MR, Ozkaynak M, Jang H. Predicting hospitalization of pediatric asthma patients in emergency departments using machine learning. Int J Med Inform. 2021;151:104468.
25. Juhn YJ, Ryu E, Wi CI, Katherine King S, Malik M, Romero-Brufau S, et al. Assessing socioeconomic bias in machine learning algorithms in health care: a case study of the HOUSES index. J Am Med Inform Assoc 2022;29:1142–51.
26. Hurst JH, Zhao C, Hostetler HP, Ghiasi Gorveh M, Lang JE, Goldstein BA.Environmental and clinical data utility in pediatric asthma exacerbation risk prediction models. BMC Med Inform Decis Mak. 2022;22(1):108.
27. Rezaeiahari M, Brown CC, Eyimina A, Perry TT, Goudie A, Boyd M, et al. Predicting pediatric severe asthma exacerbations: an administrative claims-based predictive model. J Asthma 2024;61:203–11.
28. Lee CH, Chen JC, Tseng VS.A novel data mining mechanism considering bio-signal and environmental data with applications on asthma monitoring. Comput Methods Programs Biomed. 2011;101(1):44–61.
29. Overgaard SM, Peterson KJ, Wi CI, Kshatriya BSA, Ohde JW, Brereton T, et al. A Technical Performance Study and Proposed Systematic and Comprehensive Evaluation of an ML-based CDS Solution for Pediatric Asthma. AMIA Jt Summits Transl Sci Proc. 2022;2022:25–35. Published 2022 May 23
30. Harmon I, Brailsford J, Sanchez-Cano I, Fishe J.Development of a Computable Phenotype for Prehospital Pediatric Asthma Encounters. Prehosp Emerg Care. 2025;29(1):10–21.
31. Emeryk A, Derom E, Janeczek K, Kuźnar-Kamińska B, Zelent A, Łukaszyk M, et al. Home Monitoring of Asthma Exacerbations in Children and Adults With Use of an AI-Aided Stethoscope. Ann Fam Med 2023;21:517–25.
32. Patel D, Hall GL, Broadhurst D, Smith A, Schultz A, Foong RE. Does machine learning have a role in the prediction of asthma in children? Paediatr Respir Rev. 2022;41:51–60.
33. Tsang KCH, Pinnock H, Wilson AM, Shah SA. Application of Machine Learning Algorithms for Asthma Management with mHealth: a Clinical Review. J Asthma Allergy. 2022;15:855–73.
34. Choi SG, Oh M, Park DH, Lee B, Lee YH, Jee SH, et al. Comparisons of the prediction models for undiagnosed diabetes between machine learning versus traditional statistical methods. Sci Rep 2023;13:13101.
35. Ley C, Martin RK, Pareek A, Groll A, Seil R, Tischer T.Machine learning and conventional statistics: making sense of the differences. Knee Surg Sports Traumatol Arthrosc. 2022;30(3):753–57.
36. Lowden R, Turner S.Past asthma exacerbation in children predicting future exacerbation: a systematic review. ERJ Open Res. 2022;8(4):1–17.
37. Effective Public Health Practice Project (EPHPP). Quality Assessment Tool for Quantitative Studies. 2009. Available from: https://www.ephpp.ca/quality-assessment-tool-for-quantitative-studies/. 1 Jul 2024.
38. Kothalawala DM, Kadalayil L, Weiss VB, Kyyaly MA, Arshad SH, Holloway JW, et al. Prediction models for childhood asthma: a systematic review. Pediatr Allergy Immunol 2020;31:616–27.
39. Ma L, Tibble H. Primary Care Asthma Attack Prediction Models for Adults: a Systematic Review of Reported Methodologies and Outcomes. J Asthma Allergy. 2024;17:181–94.
40. Xiong S, Chen W, Jia X, Jia Y, Liu C.Machine learning for prediction of asthma exacerbations among asthmatic patients: a systematic review and meta-analysis. BMC Pulm Med. 2023;23(1):278.
41. Xiang Y, Ji H, Zhou Y, Li F, Du J, Rasmy L, et al. Asthma exacerbation prediction and risk factor analysis based on a time-sensitive, attentive neural network: retrospective cohort study. J Med Internet Res. 2020;22(7).
42. Finkelstein J, Jeong IC.Machine learning approaches to personalize early prediction of asthma exacerbations. Ann N Y Acad Sci. 2017;1387(1):153–65.
43. Yin H, Wang K, Yang R, Tan YF, Li Q, Zhu W, et al. A machine learning model for predicting acute exacerbation of in-home chronic obstructive pulmonary disease patients. Comput Methods Programs Biomed. 2024;246:108005.
44. Zeng S, Arjomandi M, Tong Y, Liao ZC, Luo G. Developing a machine learning model to predict severe chronic obstructive pulmonary disease exacerbations: retrospective cohort study. J Med Internet Res. 2022;24(1).
45. Adibi A, Sin DD, Safari A, Johnson KM, Aaron SD, FitzGerald JM, et al. The acute COPD exacerbation prediction tool (ACCEPT): a modelling study. Lancet Respir Med 2020;8:1013–21.
46. Gu M, Liu Y, Sun H, Sun H, Fang Y, Chen L, et al. Using machine learning to predict the risk of short-term and long-term death in acute kidney injury patients after commencing CRRT. BMC Nephrol 2024;25:245.
47. Yue S, Li S, Huang X, Liu J, Hou X, Zhao Y, et al. Machine learning for the prediction of acute kidney injury in patients with sepsis. J Transl Med 2022;20:215.
48. Ahsan MM, Siddique Z. Machine learning-based heart disease diagnosis: a systematic literature review. Artif Intell Med. 2022;128:102289.
49. Battineni G, Sagaro GG, Chinatalapudi N, Amenta F.Applications of machine learning predictive models in the chronic disease diagnosis. J Pers Med. 2020;10(2):21.
50. Kumar N, Narayan Das N, Gupta D, Gupta K, Bindra J.Efficient automated disease diagnosis using machine learning models. J Healthc Eng. 2021;2021(1):9983652.
51. Sebastiani M, Vacchi C, Manfredi A, Cassone G.Personalized medicine and machine learning: a roadmap for the future. J Clin Med. 2022;11(14):4110.
52. Wu Y, Li L, Xin B, Hu Q, Dong X, Li Z.Application of machine learning in personalized medicine. Intell Pharm. 2023;1(3):152–56.
53. Mizan T, Taghipour S. Medical resource allocation planning by integrating machine learning and optimization models. Artif Intell Med. 2022;134:102430.
54. Kaliappan S, Maranan R, Malladi A, Yamsani N Optimizing Resource Allocation in Healthcare Systems for Efficient Pandemic Management using Machine Learning and Artificial Neural Networks. In: 2024 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC); 2024:1–7.
55. Fuhlbrigge A, Peden D, Apter AJ, Boushey HA, CA Jr C, Gern J, et al. Asthma outcomes: exacerbations. J Allergy Clin Immunol. 2012;129(3 Suppl).
56. Herrera-Luis E, Forno E, Celedón JC, Pino-Yanes M.Asthma Exacerbations: the Genes Behind the Scenes. J Investig Allergol Clin Immunol. 2023;33(2):76–94.
57. Castillo JR, Peters SP, Busse WW.Asthma exacerbations: pathogenesis, prevention, and treatment. J Allergy Clin Immunol Pract. 2017;5(4):918–27.
58. Jahan J, Li J, Newcomb P.Social and built environmental factors associated with adult asthma hospital admission in the North Central Texas. City Built Environ. 2024;2(1):8.
59. Akar-Ghibril N, Phipatanakul W.The indoor environment and childhood asthma. Curr Allergy Asthma Rep. 2020;20(9):43.
60. Frasca M, Torre DL, Pravettoni G, Cutica I. Explainable and interpretable artificial intelligence in medicine: a systematic bibliometric review. Discov Artif Intell. 2024;4:15.
61. Ali S, Abuhmed T, El-Sappagh S, Muhammad K, Alonso-Moral JM, Confalonieri R, et al. Explainable Artificial Intelligence (XAI): what we know and what is left to attain Trustworthy Artificial Intelligence. Information Fusion. 2023;99:101805.
62. Habiba U, Habib MK, Bogner J, Fritzsch J, Wagner S.How do ML practitioners perceive explainability? an interview study of practices and challenges. Empir Software Eng. 2025;30(1):18.
63. Ekpo RH, Osamor VC, Azeta AA, Ikeakanam E, Amos BO.Machine learning classification approach for asthma prediction models in children. Health Technol. 2023;13(1):1–10.
64. Das S, Nayak SP, Sahoo B, Nayak SC. Machine Learning in Healthcare Analytics: a State-of-the-Art Review. Arch Computat Methods Eng. 2024;31:3923–62.
65. Çorbacıoğlu ŞK, Aksel G.Receiver operating characteristic curve analysis in diagnostic accuracy studies: a guide to interpreting the area under the curve value. Turk J Emerg Med. 2023;23(4):195–98.
66. Deng F, Huang J, Yuan X, Cheng C, Zhang L.Performance and efficiency of machine learning algorithms for analyzing rectangular biomedical data. Lab Invest. 2021;101(4):430–41.
67. Dinov ID. Model Performance Assessment, Validation, and Improvement. In: Data Science and Predictive Analytics. The Springer Series in Applied Machine Learning. Cham: Springer; 2023. p. 477–531.
68. Salmi M, Atif D, Oliva D, Abraham A, Ventura S. Handling imbalanced medical datasets: review of a decade of research. Artif Intell Rev. 2024;57:273.
69. Shreffler J, Huecker MR. Diagnostic Testing Accuracy: sensitivity, Specificity, Predictive Values and Likelihood Ratios. In: StatPearls. Treasure Island (FL): StatPearls Publishing. March 6, 2023.
70. Skolnik N, Yawn BP, Correia de Sousa J, Vázquez MMM, Barnard A, Wright WL, et al. Best practice advice for asthma exacerbation prevention and management in primary care: an international expert consensus. npj Prim. Care Respir Med. 2024;34:39.


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