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ROLE OF ARTIFICIAL INTELLIGENCE IN IMPROVING ASTHMA MANAGEMENT: A SYSTEMATIC REVIEW

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ABSTRACT

Asthma affects over 339 million people globally, imposing substantial healthcare costs and reducing quality of life. While Artificial Intelligence (AI) has shown promise in healthcare, a comprehensive evaluation of its role across Asthma Management has been lacking. This systematic review, conducted following PRISMA guidelines, examined studies published between 2019 and 2024 identified through PubMed, IEEE Xplore, and Google Scholar. Sixteen studies employing Machine Learning and Deep Learning techniques were selected and assessed for methodological quality using the ROBIS tool. The review identified AI applications across three domains: predictive models for asthma persistence and exacerbation risk, diagnostic models for phenotype classification and home-based monitoring systems utilizing respiratory sound analysis and digital inhaler data. Quality assessment indicated 69% of studies demonstrated low risk of bias. Although AI offers considerable potential for improving prediction accuracy and delivering personalized care, key challenges remain, such as limited generalizability, homogeneous datasets, and insufficient real-world validation. Future research should prioritize federated learning frameworks, explainable AI techniques, and fairness-aware algorithms validated across diverse populations to ensure clinical reliability and equitable implementation in asthma care.

KEYWORDS: Artificial Intelligence in Healthcare; Asthma Monitoring; Clinical Decision Support Systems, Predictive Healthcare Analytics.

1. INTRODUCTION

Asthma is a chronic respiratory disease that affects more than 339 million people globally, according to the World Health Organization (WHO) [1], and the condition is characterized by airway constriction and inflammation, which results in significant health challenges. In addition, the annual cost of asthma in the United States alone is $80 billion, with per-patient outpatient treatment costs averaging approximately $1,291 [2,3]. Besides financial costs, asthma decreases workforce productivity through missed workdays and reduces patients' quality of life [4]. Managing asthma effectively remains challenging due to its complex and variable nature. Current approaches typically focus on symptom control and exacerbation prevention, but these strategies lack universal effectiveness. The combination of factors such as treatment adherence and environmental triggers necessitates personalized management approaches.

In this context, Artificial Intelligence (AI) has emerged as an effective tool in healthcare as it offers new possibilities for improving asthma management. AI, particularly through Machine Learning (ML), can process large amounts of data and identify complex patterns, and offer predictive insights. These capabilities have the potential for improving early detection and monitoring in real-time while offering personalized strategies for treatment in asthma care [4,5]. For example, AI-based tools can identify different at-risk individuals and predict environmental triggers besides facilitating personalized interventions, which helps in decreasing hospitalizations and improving outcomes for patients.

In spite of the hype surrounding AI-based technologies, the application of these technologies in the management of asthma is in its early stages. For example, some studies have explored specific AI methods or focused on particular aspects, such as pediatric care or prediction for exacerbation [6–8]. However, a detailed systematic review that assesses the broader role of AI across all aspects of asthma management is still lacking. That is why this systematic review is aimed at managing this gap by evaluating the role of AI in the management of asthma in detail. By analysing different AI techniques and their applications, the review seeks to show their potential and find existing limitations, while offering directions for future research. Our study not only improves understanding in this field but also offers important insights for incorporating AI into clinical practice to improve asthma care.

2. MATERIALS AND METHODS

This systematic review was carried out following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [9]. The review protocol was developed to ensure methodological transparency and reproducibility. The study selection process and outcomes are summarized in Figure 1.

2.1. Search Strategy

It is important to note that a reproducible search strategy was created according to PRISMA 2020 guidelines for finding different peer-reviewed studies that assessed the role of AI in the management of asthma. And, three major electronic databases were search including PubMed through MEDLINE, IEEE Xplore, and Google Scholar. The database searches were initially carried out on 4–5 March 2024 and were subsequently updated on 16 January 2025, which we considered the final search date for this review. To maintain a stable six-year observation window, we restricted inclusion to studies published between 2019 and 2024, even when retrieved in the January 2025 update. The coverage years for each database and relevant search strings are detailed in Supplementary Table S1.

For PubMed (MEDLINE), the following Boolean string and Medical Subject Headings (MeSH) were applied:

("asthma"[MeSH Terms] OR "asthma"[Title/Abstract]) AND ("artificial intelligence"[MeSH Terms] OR "machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "neural network*"[Title/Abstract] OR "AI"[Title/Abstract])

Filters applied: Humans, English language, and Publication years 2019–2024. The search was conducted via the PubMed platform on March 5, 2024, yielding 3,246 records.

For IEEE Xplore, the advanced search was run using the following query syntax:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Asthma" OR "Respiratory Disease")

Field restrictions were applied to Document Title, Abstract, and Index Terms. Coverage was from 2019 to 2024, with filters applied to Conference Papers and Journals only. The IEEE search was last updated on March 5, 2024, yielding 31 records. For Google Scholar, the query "Artificial Intelligence" AND "Asthma" AND ("prediction" OR "management" OR "diagnosis") was executed. Google Scholar was primarily used to locate grey literature, non-indexed conference proceedings, and preprints not found in

PubMed or IEEE Xplore.

Additionally, we performed backward and forward citation chaining on the studies that met the inclusion criteria after database screening. Citation chaining of the 12 database-identified studies yielded four further eligible articles that had not been retrieved by the initial searches, resulting in a final total of 16 studies included in the review. In total, 52,889 records were retrieved across all sources (PubMed n = 3,246; IEEE Xplore n = 31; Google Scholar n = 49,600; citation chaining n = 12). After removal of 4,329 duplicate entries, 48,560 unique records remained for screening. All records were managed in EndNote 20 for de-duplication and reference tracking. The detailed database-specific search strategies, including Boolean logic, field tags, truncation/wildcards, and platform coverage, are presented in Supplementary Table S1 for full transparency and reproducibility.

2.2. Eligibility Criteria

The inclusion criteria include the eligibility criteria for this review were designed to make sure that all included studies offered empirical and reproducible evidence about the application of AI techniques in the management of asthma. Only the written and published in the English language were considered, for maintaining consistency in terminology and facilitating accurate interpretation, and making sure that all methodological and technical aspects could be evaluated in a reliable manner.

To be eligible for inclusion, studies had to directly examine or implement AI or machine learning (ML) methods in the context of asthma management. This criterion encompassed a broad range of applications, including diagnosis and classification, prediction of exacerbations, disease risk modeling, patient monitoring, treatment optimization, and clinical decision support. The review focused specifically on studies that developed, validated, or applied AI algorithms to asthma-related data with measurable outputs. Papers that only discussed AI in a conceptual, narrative, or theoretical sense, or those that simply reviewed existing literature without empirical analysis, were excluded to maintain a clear focus on data-driven evidence.

The review emphasized the inclusion of empirical and model-development studies. In this context, "empirical" refers to any study in which AI models were trained, tested, or validated using real-world datasets, clinical data, or simulated datasets that contained measurable health-related variables. This definition differs from the biomedical sense of "experimental," which generally refers to interventional or laboratory studies [10]. Accordingly, both retrospective analyses (for example, secondary analyses of electronic health records or imaging datasets) and prospective studies (such as trials or pilot implementations of AI tools) were considered eligible, provided that an AI model or algorithm was applied in a reproducible and data-driven manner.

As an additional inclusion consideration, we prioritized studies that reported a quantitative assessment of AI model accuracy, predictive validity, or diagnostic capability. Performance evaluation was defined according to accepted practices in biomedical AI research, including the use of internal validation methods such as k-fold cross-validation, holdout or split-sample testing, or bootstrapping, as well as external validation using independent datasets where available. Studies were expected to report at least one recognized performance metric such as accuracy, area under the curve (AUC), sensitivity, specificity, precision, recall, or F1-score. However, we also included a small number of implementations-focused studies in which AI was embedded in clinical workflows but formal predictive metrics were not available; in these cases, we required clearly reported qualitative or practical outcomes (e.g., workflow efficiency, adherence, or quality of life), and these studies were analysed narratively in the Results section [11].

It is important to recognize that interventional or randomized controlled trials using AI-based decision-support systems were included where available because they offered high-level evidence of clinical utility. However, purely observational descriptive studies that did not involve the implementation or testing of an AI model were excluded, even if they discussed asthma-related data. Moreover, theoretical and editorial papers, review articles, commentaries, and conference abstracts that did not have methodological or performance details were excluded for ensuring methodological rigor.

The exclusion criteria involve:

- Articles that were not available in full text, or were behind restricted access without sufficient methodological or results details for evaluation.
- Papers that discussed asthma management or treatment but did not really integrate artificial intelligence or its subfields (e.g., machine learning, deep learning, or data-driven modeling) [12].
- Studies that focused exclusively on general respiratory conditions such as COPD and

pneumonia were excluded unless asthma was explicitly included as a distinct diagnostic category or asthma-specific outcomes could be clearly disaggregated from the model outputs.

- Duplicate publications or studies presenting overlapping datasets from the same research group; in such cases, only the most comprehensive or recent version was retained for inclusion [13].
- Non-English language publications, reviews, editorials, or conference abstracts lacking empirical results were also excluded for maintaining methodological consistency.

2.3. Study Selection Process

In accordance with the PRISMA 2020 guidelines, a comprehensive multi-stage screening process was carried out. In total, 52,889 records were retrieved across all sources (PubMed n = 3,246; IEEE Xplore n = 31; Google Scholar n = 49,600; citation chaining n = 12). After removal of 4,329 duplicate entries, 48,560 unique records remained in the dataset. All records were managed in EndNote 20 for de-duplication and reference tracking. The numbers and reasons for exclusions at each stage are shown in Figure 1 and summarized in Table 2. Language restrictions were applied to include only English-language articles, which was also reflected in the exclusion counts [14].

2.4. Risk Of Bias Assessment

To improve the methodological aspect of this systematic review, a formal evaluation of study quality and risk of bias was carried out using an adapted risk-of-bias framework informed by the ROBIS (Risk of Bias in Systematic Reviews) domains. Because ROBIS was originally developed for assessing systematic reviews rather than primary prediction or diagnostic studies, we tailored its four domains to the context of AI-based model-development and evaluation studies. Two independent reviewers applied this adapted checklist to each study, with disagreements resolved through consensus. [15]. The assessment ensured that the findings of this review are confirmed by reproducible and transparent procedures of quality management.

Table 1: Quality Assessment of Included Studies.

Study ID	Study Design	Dataset Type	Validation Approach	Risk of Bias (adapted framework based on ROBIS domains)	Overall Quality Rating	Key Notes
[18] Personalized prediction of early childhood asthma persistence	Retrospective cohort	Clinical & demographic data (9,934 records)	10-fold cross-validation	Low risk	**High**	Large, diverse dataset; robust internal validation.
[19] ML-Based Asthma Risk Prediction (IoT + Smartphones)	Experimental prototype	IoT & environmental sensor data	Split-sample validation	Moderate risk	**High**	Real-world environmental integration; missing sensitivity values.
[20] Predictive ML Tool for Asthma Exacerbations (eMDPI)	Prospective observational	Digital inhaler data (360 patients)	External validation	Low risk	**High**	Clear outcome measures; validated on external data.
[21] ML-Enhanced HRCT Analysis (Pediatric)	Retrospective diagnostic	Imaging (HRCT) data (41 patients)	Internal validation	Moderate risk	**Medium**	Small sample size; strong diagnostic metrics.
[22] ML Model for Allergic/Non-Allergic Asthma	Experimental	Clinical & lab data (127 patients)	5-fold cross-validation	Moderate–High risk	**Medium–Low**	Limited dataset; partial metric reporting.
[23] DL Prediction of Hospital Readmissions for Asthma/COPD	Retrospective EHR study	EHR data (5,794 patients)	Split-sample validation	Low risk	**High**	Large dataset; robust performance (AUC 0.83).

[24] AI Approach to Monitoring Respiratory Sounds	Cross-sectional experimental	Acoustic recordings (899 patients)	10-fold cross-validation	Low risk	**High**	Reliable AUC 0.94; sound-based remote monitoring.
[25] Prediction Model of Child Asthma Risk (Family Data)	Population-based cohort	Family history & EHR (195,666 records)	External validation	Low risk	**High**	Very large dataset; excellent generalizability.
[26] AI-Assisted Clinical Decision Support (Pediatric)	Randomized clinical trial	EHR data (184 participants)	Controlled trial validation	Low risk	**High**	RCT design; moderate sample but strong control.
[27] Home-Based Digital Assessments (Sentiment & Emotion AI)	Pilot feasibility study	Video and text data from patients	Not stated (N/A)	Moderate -High risk	**Medium**	Innovative QoL monitoring; lacks validation.
[28] AI-Powered Thermal Imaging Prediction	Experimental	Thermal breathing images (benchmark dataset)	Internal validation	Moderate risk	**Medium–High**	High accuracy; dataset details limited.
[29] Classification of Lung Disease (Deep Learning)	Retrospective diagnostic	Annotated CT images	External validation	Low risk	**High**	Good transfer-learning design; reproducible results.
[30] Voice Analysis Framework for Asthma–COVID-19 Diagnosis	Experimental	Vocal audio + mobile cloud data	Internal validation	Moderate risk	**Medium**	Innovative multimodal data; small sample.
[31] Advanced Ensemble Learning for Asthma Prediction	Retrospective cohort	EHR (29,396 patients)	Split-sample & cross-validation	Low risk	**High**	Ensemble approach; strong accuracy (90%).
[32] MeLoDicA Audio-Based Asthma Detection	Experimental	Vocal recordings (N/A)	10-fold cross-validation	Low–Moderate risk	**Medium–High**	Good performance (92% accuracy); limited dataset.
[33] AI Sound Recognition on Medication Adherence	Benchmark evaluation	Audio data (RDA Suite)	Benchmark comparative testing	Low risk	**High**	Standardized benchmark use; reproducible metrics.

The methodological quality of each included study was assessed using the ROBIS (Risk of Bias in Systematic Reviews) tool, which was adapted for model-development and AI-based studies. Each study was assessed across four domains: (1) study eligibility criteria, (2) identification and selection of studies, (3) data collection and study appraisal, and (4) synthesis and findings. For each domain, risk judgments (low, moderate, or high) were recorded together with a one-line justification, as shown in Supplementary Table S2.

The overall results indicated that 11 of 16 studies (69%) were judged as low risk of bias, mainly due to transparent dataset descriptions, valid inclusion criteria, and effective validation approaches (internal or external). Four studies (25%) showed moderate risk, often due to incomplete metric reporting or unclear recruitment strategies, while one study (6%) was rated as moderate–high risk, reflecting limited data transparency and missing validation. Figure 2 presents a ROBIS "traffic-light" summary showing the distribution of judgments across all domains.

2.5. Ethical Considerations

This study is a systematic review and does not involve human or animal subjects, which is why an ethical approval was not needed. However, care was taken in using different credible sources for getting data [16]. This detailed methodology ensured the review would offer reliable insights into the uses of AI in the management of asthma while allowing reproducibility and making a base for future research [17].

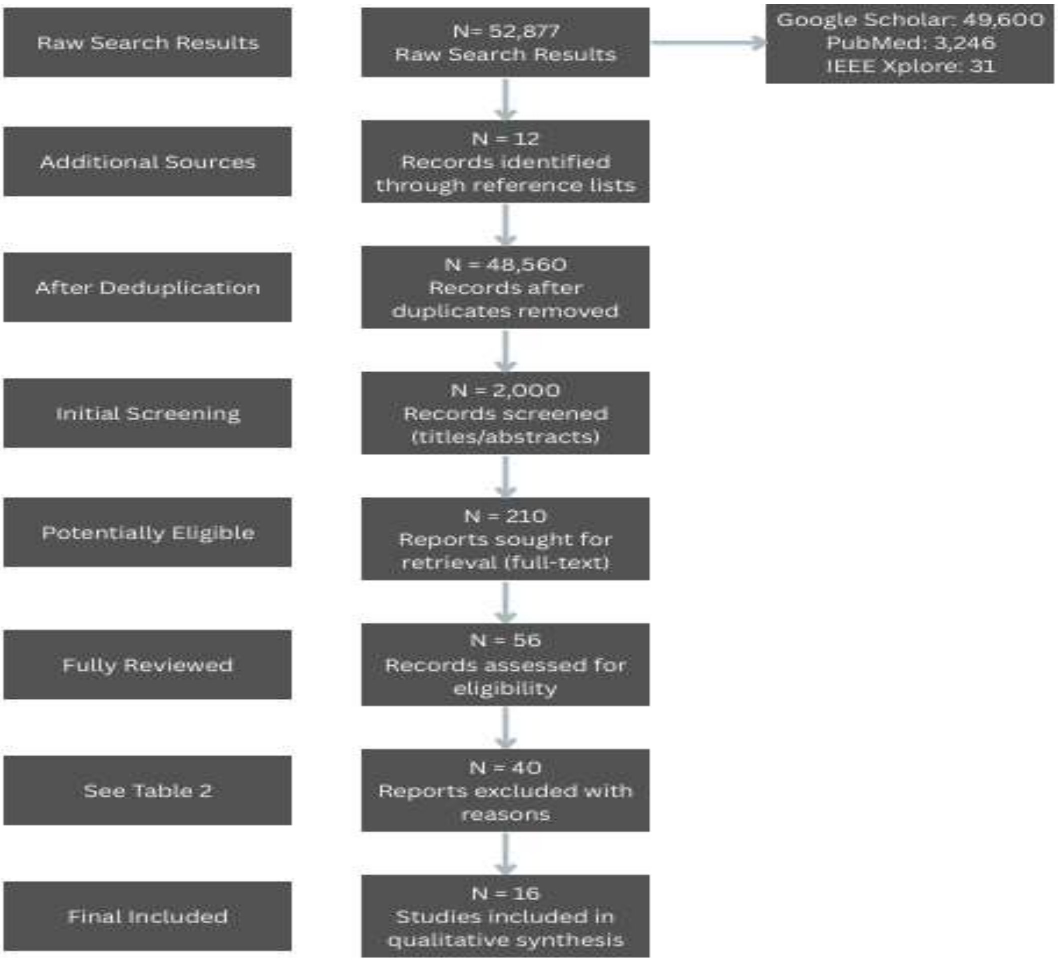

Figure 1: Prisma Flowchart Diagram.

Table 2: Reasons For Exclusion at the Full-Text Review Stage.

Exclusion Reason	Number of Studies Excluded
Non-English language	4
Not specific to asthma (general respiratory diseases only)	6
Review, editorial, or theoretical paper	10
Missing methodological details or performance metrics	8
Duplicate or overlapping dataset	4
Limited access (no full text)	5
Other (e.g., unclear AI application)	3
Total	**40**

3. RESULTS

Other than the PRISMA flow diagram, it is important to recognize that the distribution of AI techniques and their application of domains across the included studies is summarized in Figure 2. Different machine learning methods such as Gradient Boosting, XGboost, and Random Forest were the most frequently applied approaches, followed by architectures of deep learning such as CNNs and multi-layered perceptrons. Voice-recognition and sound analysis based on AI also showed great relevance in adherence assessment and asthma monitoring. Regardless, emerging applications such as IoT integration, thermal imaging, and NLP show the increasing diversity of AI methodologies being used in the management of asthma between 2019 and 2024.

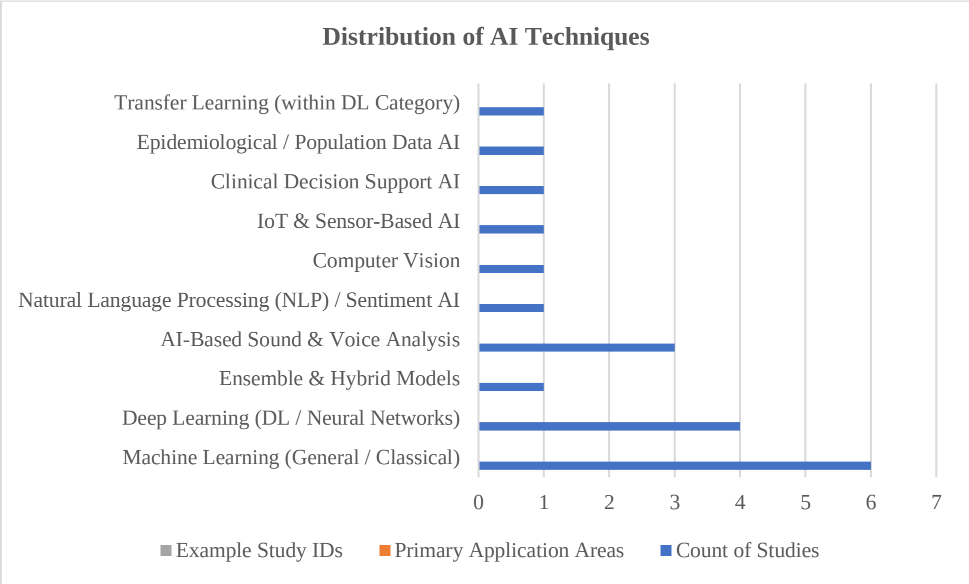

Figure 2: Distribution Of AI Techniques.

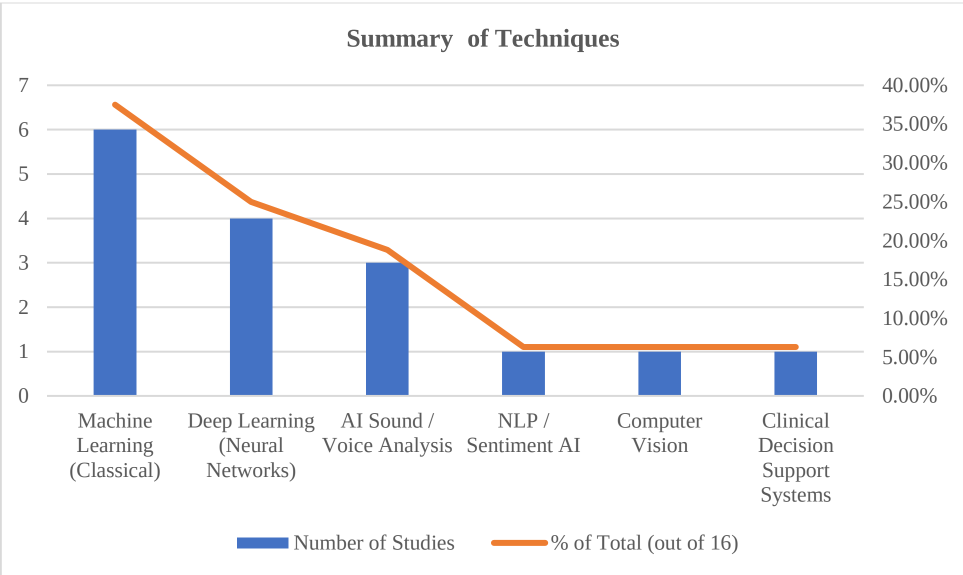

Figure 3: Distribution of AI Techniques Simplified.

Considering the methodological diversity among the included studies, findings are organized by AI technique and application area. This categorization facilitates thematic synthesis despite the heterogeneity in AI models and performance metrics among others. The systematic review included 16 studies after applying all the exclusion criteria. These studies focused on different AI techniques for managing different areas of asthma and other respiratory diseases, Table 3. The research showed the effectiveness of several AI methods ranging from AI and Deep Learning (DL) in the improvement of diagnosing and managing asthma. Different AI techniques have been used to address the multiple challenges that affect asthma care. For example, some studies applied ML models for predicting the exacerbations of asthma and improving the timing and effectiveness of different interventions. Meanwhile, other studies focused on the use of DL techniques for analyzing medical images, such as CT scans, and accurately classifying different lung diseases such as asthma and pneumonia among others.

Furthermore, voice analysis was another area where AI showed significant potential because several studies used AI for detecting changes in vocal patterns, which can be quite an early sign of attacks of asthma or other respiratory issues. This approach is capable of helping in monitoring patients at home and offering early warnings of possible health issues.

AI was also used for monitoring adherence to medication. By analysing the sounds produced by patients during the use of inhalers, AI systems can evaluate if patients are using their inhalers in a correct manner, which is quite important for the proper management of asthma.

Table 3: Comparison And Synthesis of AI Techniques and Applications in Asthma Management (2019-2024).

Study Title	Year	Study Design	AI Technique	Application Area	Sample Size	Outcomes
Personalized prediction of early childhood asthma persistence [18]	2021	Prediction-model development and internal validation (retrospective cohort)	XGBoost, Feature Importance Analysis	Predicting asthma persistence in children	9,934	XGBoost model predicted the persistence of asthma on the basis of different features like age of diagnosis and prior health use.
Machine Learning-Based Asthma Risk Prediction Using IoT and Smartphone Applications [19]	2021	Mobile app/tool evaluation with embedded model-development	CNN, IoT Integration	Risk prediction of asthma attacks	N/A	CNN-based app predicted the risk of asthma using PEFR values and indoor PM, and weather data. It was capable of outperforming DNN methods.
Predictive ML Tool for Asthma Exacerbations (eMDPI study) [20]	2022	Prediction-model development and internal validation study	Gradient-Boosting Trees	Predicting asthma exacerbations	360	The developed model estimated exacerbations with the use of digital inhaler data with an ROC AUC of 0.83.
ML-Enhanced HRCT Analysis for Pediatric Asthma Diagnosis [21]	2024	Diagnostic-accuracy study (cross-sectional imaging dataset)	Random Forest, Classification Trees	Diagnosis and severity assessment	41	ML models using HRCT features like AWT were capable of achieving 95% sensitivity and specificity, and accuracy for severe asthma.
ML Model for Allergic and Non-Allergic Asthma Classification [22]	2022	Prediction-model development and internal validation	Support Vector Machines (SVM), Logistic Regression	Classification of asthma types	127	SVM achieved an accuracy of 77.8% in classifying allergic vs. non-allergic asthma with nine features.
Deep learning prediction of hospital readmissions for asthma and COPD [23]	2023	Retrospective observational model-development and external validation study	Multilayer Perceptron (Deep Learning)	Predicting hospital readmissions	5,794 patients	Multilayer perceptron performed better than traditional ML models in the prediction of readmissions with the use of EHR data, showing the effectiveness of deep learning in the identification of high-risk asthma and COPD patients.
Artificial Intelligence Approach to the Monitoring of Respiratory Sounds in Asthmatic Patients [24]	2022	Prospective monitoring and algorithm-validation study	AI-based sound analysis	Monitoring respiratory health at home	9,319 recordings from 899 patients	AI distinguished between asthma patients reliably with and without abnormal breath sounds, with high accuracy (AUC up to 0.94). This shows potential for AI-based tools in monitoring of

						symptoms of asthma at home, which decreases the need for frequent visits to the doctor.
Developing a prediction model of children asthma risk using population-based family history data [25]	2023	Population-based prediction-model development and validation study	LASSO Logistic Regression, Random Forest	Predicting asthma risk in children	195,666 children	Including parental and child comorbidities in different prediction models improved sensitivity and specificity. Random Forest and LASSO logistic regression identified different main predictors such as parental asthma and the allergic conditions of children.
AI-assisted clinical decision support for childhood asthma management [26]	2021	Prospective interventional tool-evaluation (clinical decision-support pilot)	Machine Learning (A-GPS)	Clinical decision support for pediatric asthma	184 participants	A-GPS decreased the time for EHR review and showed cost savings, though there was no major difference in the frequency of exacerbation compared to the control group. The intervention helped with timelier follow-up after exacerbations.
Home-based Digital Assessments with Sentiment & Emotion AI [27]	2021	Proof-of-concept digital-health evaluation study	Sentiment and Emotion Analysis (NLP)	Quality-of-life tracking in asthma patients	N/A	Sentiment analysis of video and text messages identified and found subtle QoL changes, connecting with traditional measures. This approach showed potential for early detection of improved control over asthma through digital devices and AI use in clinical trials.
Predicting Asthma Attacks Through AI-Powered Thermal Imaging Analysis [28]	2024	Diagnostic-accuracy and feasibility study	AI and Computer Vision	Non-invasive asthma attack prediction	Benchmark dataset (size not disclosed)	AI-based thermal imaging got almost perfect accuracy (99.49%) in predicting the attacks of asthma through the analysis of different nasal thermal patterns. This method is non-invasive and improves patient comfort, and also shows potential for broad accessibility in the management of asthma.
Classification of Lung Disease with	2024	Prediction-model development and	Transfer Learning, Xception Model	Classification of lung diseases	Annotated medical images	The study developed AI models with the

Recommendation using Deep Learning [29]		internal validation (cross-sectional imaging)		(COVID-19, pneumonia, TB, etc.) using CT scans		use of deep learning for classifying lung diseases, including COVID-19. The Xception model improved accuracy in disease classification, especially differentiating COVID-19 from pneumonia and other respiratory conditions, which supports early diagnosis.
Voice Analysis Framework for Asthma-COVID-19 Early Diagnosis and Prediction [30]	2021	Model-development and mobile-app evaluation study	AI-based voice analysis, Mobile Cloud Computing	Early detection and prediction of asthma and COVID-19 through voice analysis	N/A	The study offered an AI system for analyzing and evaluating voice parameters for identifying asthma attacks and COVID-19. This approach with the use of mobile cloud computing aimed to offer early disease detection. The proposed system can monitor the symptoms of both asthma and COVID-19 through vocal changes.
Advanced Ensemble Learning Approach for Asthma Prediction: Optimization and Evaluation [31]	2024	Prediction-model development and internal validation study	Decision Tree, Random Forest, Gradient Boosting	Predicting asthma exacerbations	29,396 asthma patients	The ensemble model tends to combine a number of ML techniques ranging from decision trees to gradient boosting and it got 90% accuracy in predicting the exacerbations of asthma. This suggests the potential for more accurate prediction of asthma, which can lead to better management and fewer exacerbations.
MeLoDicA AI-Machine Learning Based Detection of Asthma via Vocal Audio Analysis [32]	2024	Diagnostic-accuracy study using audio datasets	Random Forest, SVM, KNN	Asthma detection via audio analysis	N/A	The study introduced a unique method using ML algorithms for detecting asthma from vocal recordings. The highest accuracy of 92% was achieved with the use of Random Forest on the features of vowel pronunciation. It shows a change towards more

						effective methods of detection of asthma without medical devices.
AI Sound Recognition on Asthma Medication Adherence: Evaluation With the RDA Benchmark Suite [33]	2023	Model-development and performance-evaluation study	Machine Learning, Deep Networks	Medication adherence assessment via sound recognition	N/A	The study analyzed ML models for evaluating adherence to asthma medication by evaluating inhalation sounds. It proposed a benchmarking suite (RDA Suite) for improving the detection of medication use and adherence, which offers potential improvements for the management of patients and monitoring of adherence using sound-based methods.

Table 4: Summary of Evaluation Metrics Across Studies.

Study ID	**AI Technique**	**Evaluation Metric(s) Reported**	**Reported Performance**	**Evaluation Dataset / Sample Size**	**Notes on Metric Consistency**
[18] Personalized prediction of early childhood asthma persistence	XGBoost	Accuracy, AUC	Accuracy 0.86; AUC 0.91	9,934 children's clinical data	Complete reporting of both metrics – robust internal validation.
[19] ML-Based Asthma Risk Prediction (IoT)	CNN	Accuracy only	0.94 accuracy (outperformed DNN)	IoT + environmental dataset (N/A)	Lacks sensitivity/specificity values.
[20] Predictive ML Tool for Asthma Exacerbations (eMDPI)	Gradient Boosting Trees	AUC, ROC	AUC 0.83	Digital inhaler data (360 patients)	Strong metric clarity with external validation.
[21] ML-Enhanced HRCT Analysis (Pediatric Asthma)	Random Forest	Sensitivity, Specificity, Accuracy	95% for each metric	HRCT images (41 patients)	Comprehensive diagnostic reporting.
[22] ML Model for Allergic vs Non-Allergic Asthma	SVM / Logistic Regression	Accuracy only	0.778 accuracy	127 patients	Partial metric reporting; limited comparison.
[23] DL Prediction of Hospital Readmissions	Multilayer Perceptron (DL)	AUC only	AUC 0.83	EHR data (5,794 patients)	Single metric reported; no baseline accuracy.
[24] AI Approach to Monitoring Respiratory Sounds	AI Sound Analysis	AUC, Accuracy	AUC 0.94; Accuracy ~0.93	899 patients, 9,319 recordings	Well-reported metrics; robust performance.
[25] Prediction Model of Children Asthma Risk	LASSO LR / Random Forest	Sensitivity, Specificity	>0.85 each	195,666 children	No accuracy or AUC reported; good comparative clarity.
[26] AI-Assisted Clinical Decision Support	ML (A-GPS)	Clinical outcome change (Cost & EHR review time)	Reduced review time; no accuracy reported	184 participants RCT	Non-predictive metrics – qualitative comparison only.
[27] Home-Based Digital Assessments (Sentiment AI)	NLP (Sentiment/Emotion)	Correlation with QoL scores	Moderate positive correlation ($p<0.05$)	N/A	No AI performance metric; behavioral output based.

[28] AI-Powered Thermal Imaging Prediction	Computer Vision	Accuracy only	0.9949 accuracy	Benchmark thermal dataset (N/A)	Extremely high accuracy; no AUC reported.
[29] Classification of Lung Disease (Deep Learning)	Xception Model (Transfer Learning)	Accuracy only	0.97 accuracy	Annotated CT images	Clear single metric; reproducible design.
[30] Voice Analysis Framework for Asthma-COVID-19	AI Voice + Cloud Computing	Accuracy only	~0.90 accuracy	Vocal dataset (N/A)	No AUC or sensitivity values provided.
[31] Advanced Ensemble Learning Approach	Decision Tree + RF + GB Ensemble	Accuracy, F1-Score	Accuracy 0.90; F1 0.88	29,396 asthma patients	Comprehensive dual-metric reporting.
[32] MeLoDicA Audio-Based Asthma Detection	Random Forest, SVM, KNN	Accuracy only	0.92 accuracy (RF best)	Audio dataset (N/A)	Good accuracy; no cross-metric comparison.
[33] AI Sound Recognition on Medication Adherence	ML / Deep Networks	Accuracy, Precision, Recall	Accuracy 0.91; Precision 0.89; Recall 0.87	RDA benchmark suite (N/A)	Comprehensive reporting and benchmark standardization.

The included studies in Table 1 showed significant heterogeneity in AI model types (e.g., support vector machines, convolutional neural networks), data sources (e.g., electronic health records, spirometry), and outcome measures (e.g., accuracy and F1-score). This variability decreased our ability to synthesize findings in a quantitative manner. Consequently, we considered a thematic synthesis that grouped studies by application area, which allowed for a more coherent comparison. While this approach facilitates interpretability, it also highlights the need for standardized evaluation metrics and reporting practices in future research.

In addition to it, Table 4 offers a synthesis of different evaluation metrics that were reported in the included studies. There is a large variability as some studies reported only AUC or accuracy while others offered comprehensive diagnostics metrics including F1-score, specificity, and sensitivity. For improving interpretability, F1-score, AUC, and accuracy were prioritized for comparative synthesis. Moreover, studies that lacked quantitative measures such as [26] and [27] were assessed qualitatively for methodological effectiveness. This shows the critical need for standardized frameworks for performance reporting in asthma research that involves the use of AI.

4. DISCUSSION

The increasing use of AI in the management of asthma shows the potential for improving not only the diagnosis but also the outcomes of treatment. For example, the 16 studies evaluated in this systematic review offer critical insights into the different methods and their applications.

4.1 Predictive Models

Actually, a number of studies have used ML and DL models for predicting the exacerbations and risk of asthma. For example, [18] used an XGBoost model for predicting the persistence of asthma by assessing different features such as the age of diagnosis and prior use of healthcare. In fact, this approach showed the potential for proper predictions by using demographic and historical data. Similarly, [19] expounded an application of Convolutional Neural Networks (CNN) that uses PEFR values and indoor Particulate Matter (PM). It mainly outperformed methods based on Deep Neural Networks (DNN) in predicting the risk of asthma. The use of environmental factors in this study place emphasis on the importance of contextual data in improving the accuracy of prediction.

In contrast, [20] focused on the exacerbations of asthma with the use of data from digital inhalers and got a ROC AUC of 0.83. Even though this model shows potential for predicting exacerbations, its dependence on the usage data of digital inhalers decreases its applicability to patients who do not really use such devices in a consistent manner. In addition, [25] further explored the prediction of asthma risk by using family history data based on population and comorbidities with the use of LASSO Logistic Regression (LR) and Random Forest (RF) models. It should be noted that including both the comorbidities of children and parents improved the specificity and sensitivity of the models. It shows the importance of both familiar and genetic factors.

4.2 Diagnostic Models

Different studies that focused on diagnostic challenges used a number of AI techniques for classifying the subtypes of asthma and evaluating their severity. For example, [21] showed the use of ML-facilitated HRCT or high-resolution computed tomography analysis for the diagnosis of asthma in children. The model identified changes in the structural airway and achieved both accuracy and high sensitivity without a problem. A non-invasive approach is offered by this method to the identification of different phenotypes of asthma, which are capable of guiding personalized interventions.

Moreover, [22] used Support Vector Machines (SVM) for classifying asthma that is allergic versus non-allergic among preschool children achieving an accuracy of 77.8%. The use of nine features for classification shows the role of feature selection in the improvement of different diagnostic models. And [23] used a DL model of multilayer perceptron for predicting readmissions to hospitals for COPD and asthma, and it outperformed traditional methods of ML. The success of this model shows the potential of DL in the evaluation of complex data from EHRs for the identification of high-risk patients.

4.3 Monitoring And Home-Based Evaluations

It can be said that AI-based tools for monitoring asthma symptoms and optimizing the management of diseases have obtained a lot of attention in clinical research. [24], for example, offered an AI system for the analysis of respiratory sounds that were recorded with the use of stethoscope auscultation. The system got high values of AUC and it can properly distinguish between the patients of asthma with and without sounds that are abnormal. This approach could allow remote monitoring and decrease the need for in-person consultations that are frequent. Moreover, [26] tested an A-GPS or clinical decision support tool based on AI for the management of childhood asthma. Even though the intervention decreased the review time of EHR and resulted in cost savings, it did not really alter the frequencies of exacerbation. This finding shows that even though AI can improve clinical workflows, more optimization may be needed for affecting different clinical outcomes. It should be noted that [27] evaluated sentiment and emotion AI for evaluating the changes in QoL or quality of life changes for asthma patients through electronic questionnaires and video recordings. Even though this method detected improvements in QoL, different interpersonal changes and biases in the emotional analysis derived from the video showed the need for calibration that is personalized.

4.4 Gaps and Challenges

It should be noted that many studies relied on specific datasets such as the use of digital inhalers (study [20]) or HRCT scans (study [21]). These approaches may not really generalize to larger populations, especially in settings with low resources, which is why expanding datasets for including real-world scenarios and diverse populations is quite important. Even though studies like [19] and [25] used environmental and familial data, there is still a gap in combining these factors with socio-economic and behavioral data for better risk assessment. Despite their high accuracy, different models such as CNNs and DLs [19, 23] often lack in interpretability, which poses challenges for proper adoption. Transparent AI models that are explainable are important for getting clinicians' trust and improving use in daily practice. Even though several AI models showed high accuracy in controlled environments, their clinical adoption is limited and the AI applications are largely experimental. Very few studies included external validation across different healthcare systems or populations, and even fewer were tested in clinical settings with end-user involvement [20]. This gap shows the need for implementation research and regulatory frameworks that support safe integration into existing care models.

Several AI techniques that depend on advanced imaging [21] or digital devices [20] may not be accessible to all patients. That is why developing cost-effective and easy solutions is important for making sure that asthma management is equitable. Even though tools that are home-based [24, 27] provide important data, there is limited evidence on their impact on asthma outcomes in the long run. That is why future research should be exploring how continuous monitoring and interventions in real time affect disease control.

In addition, in spite of promising results, few of the reviewed AI models have undergone prospective validation or clinical trials. The majority remain in the proof-of-concept phase or rely on retrospective datasets, which highlights concerns about generalizability and effectiveness in practical settings [28]. Bridging this gap requires more collaborative efforts between AI developers and clinicians. Some pilot studies have begun exploring AI integration into asthma clinics for symptom prediction and adherence monitoring, but these are still in early stages. The lack of clinical adoption highlights the importance of usability and integration into existing pathways of care.

Moreover, studies like [27] identified biases in emotion analysis while others [23] highlighted differences in rates of readmission across different demographic groups. To ensure the ethical deployment of AI applications and prevent inequalities, it is crucial that algorithmic biases are opportunely recognized and managed. The ROBIS assessment revealed that while most included studies demonstrated low overall risk of bias, a considerable proportion exhibited moderate or unclear risks, particularly regarding dataset transparency and validation reporting. Consequently, the overall certainty of the evidence is considered moderate, and the review's conclusions should be interpreted cautiously. Future AI-asthma research should prioritize standardized reporting and transparent data pipelines, and external validation to improve reproducibility and reduce bias.

4.5 Future Directions

Combining diverse data that ranges from environmental to genetics can help in improving the predictive and diagnostic abilities of AI models. Moreover, the availability of interpretable models is likely to improve clinical acceptance and facilitating use in the workflows of asthma management. And, extra efforts should be made for making affordable and user-friendly tools that suit diverse groups, especially in settings that have low resources. The evaluation of the effectiveness of AI-based interventions in the long run can be helpful in offering better insights into their effect on the outcomes of patients and asthma control. And, stricter guidelines for minimizing biases and ensuring the ethical use of AI will be important for increasing trust.

Furthermore, future research should be studying federated learning frameworks that allow multi-centre model training on distributed hospital datasets while preserving patient privacy and complying with data-protection laws. At the same time, equally important is the systematic adoption of explainable-AI techniques such as SHAP values, counterfactual explanations, and prototype-based networks for creating clinician-friendly rationales and increasing patient trust. Dedicated studies are also required to develop and validate fairness-aware algorithms that proactively detect and mitigate bias across demographic groups. Finally, we recommend the creation of ethical-governance roadmaps (covering data stewardship, informed consent for AI-driven interventions, and post-deployment monitoring) to guide safe integration of AI tools into routine asthma care.

5. CONCLUSIONS

In this systematic review, the increasing role of AI in managing asthma has been revealed. ML and DL techniques such as CNNs and SVMs have been effectively used in addressing challenges such as predicting the persistence of asthma and classifying asthma types. Moreover, AI has also been applied to different innovative areas such as respiratory sound monitoring and evaluation of chest imaging for assessing the severity of asthma. The integration of EHR data and comorbidity information has significantly improved the precision of risk prediction models. AI-based decision support systems and digital therapeutics combining patient data and emotion AI show potential for transforming asthma care through home-based and personalized interventions.

Despite these promising approaches, gaps remain in their widespread application. Most AI models focus on specific aspects of asthma management and lack generalizability across diverse populations. Data collection biases and limited feature sets may pose challenges and constrain real-world implementation. Addressing these gaps requires better datasets and validation procedures in both clinical and real-world settings.

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APPENDIX

Supplementary Table S1: Full Search Strategies and Database Details

Database / Platform	Coverage Years	Date Last Searched	Boolean String (Field Tags, MeSH Terms, Operators, Truncation)	Filters / Limits Applied	Records Retrieved	Notes
PubMed (via MEDLINE)	2019 – 2024	First searched 4–5 March 2024; updated 16 January 2025	("asthma" [MeSH Terms] OR "asthma" [Title/Abstract]) AND ("artificial intelligence" [MeSH Terms] OR "machine learning" [Title/Abstract] OR "deep learning" [Title/Abstract] OR "neural network*" [Title/Abstract] OR "AI" [Title/Abstract])	English language; Humans; 2019–2024 publication years	3,246	Used both MeSH and keyword searching; searched via PubMed platform.
IEEE Xplore	2019 – 2024	First searched 4–5 March 2024; updated 16 January 2025	("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Asthma" OR "Respiratory Disease")	Journals and Conference papers only	31	Fields restricted to Title, Abstract, and Index Terms.
Google Scholar	2019 – 2024	First searched 4–5 March 2024; updated 16 January 2025	"Artificial Intelligence" AND "Asthma" AND ("prediction" OR "management" OR "diagnosis")	First 200 results screened; sorted by relevance	49,600	Used for grey literature and non-indexed conference papers.
Citation Chaining and References	N/A	First searched 4–5 March 2024; updated 16 January 2025	Manual backward and forward citation tracking of included studies	None	4 additional eligible studies identified	Ensured completeness and captured missed relevant articles.

Supplementary Table S2: ROBIS Risk-Of-Bias Assessment for Included Studies.

Study ID / Reference	Domain 1: Study Eligibility Criteria	Domain 2: Identification & Selection of Studies	Domain 3: Data Collection & Appraisal	Domain 4: Synthesis & Findings	Overall ROBIS Judgment
[18] Personalized prediction of early childhood asthma persistence	Low – Clear inclusion/exclusion and pediatric focus	Low – Dataset defined and comprehensive	Low – Consistent data preprocessing, cross-validation applied	Low – Results well supported by data	Low
[19] ML-Based Asthma Risk Prediction (IoT + Smartphones)	Low – Clear focus on AI-based risk prediction	Moderate – No details on sample recruitment	Moderate – Limited metric reporting	Low – Logical interpretation of results	Moderate
[20] Predictive ML Tool for Asthma Exacerbations (eMDPI)	Low – Explicit inclusion/exclusion	Low – Transparent patient selection	Low – External validation ensures reliability	Low – Findings consistent with reported data	Low

[21] ML-Enhanced HRCT Analysis (Pediatric)	Moderate – Limited diagnostic inclusion detail	Low – Clear image-based selection	Moderate – Small sample, potential overfitting	Low – Results valid but not generalizable	Moderate
[22] ML Model for Allergic/Non-Allergic Asthma	Moderate – Lacks reproducible inclusion criteria	Moderate – Unclear recruitment process	High – Limited dataset, incomplete reporting	Moderate – Interpretation reasonable	Moderate–High
[23] DL Prediction of Hospital Readmissions	Low – Well-defined retrospective EHR inclusion	Low – Systematic extraction process	Low – Split validation increases confidence	Low – Clear synthesis and performance metrics	Low
[24] AI for Monitoring Respiratory Sounds	Low – Clear inclusion of asthmatic patients	Low – Adequate sampling of audio data	Low – Sufficient validation and outcome metrics	Low – Strong data–conclusion linkage	Low
[25] Prediction Model Using Family Data	Low – Population-based inclusion transparent	Low – Cohort comprehensively defined	Low – External validation and performance metrics robust	Low – Conclusions data-driven	Low
[26] AI-Assisted Clinical Decision Support	Low – RCT design with clear inclusion/exclusion	Low – Controlled participant allocation	Low – Transparent data handling	Low – Direct linkage between evidence and claims	Low
[27] Home-Based Digital Assessments (Sentiment & Emotion AI)	Moderate – Limited eligibility reporting	Moderate – Convenience sampling	High – No clear validation	Moderate – Qualitative synthesis only	Moderate–High
[28] AI-Powered Thermal Imaging Prediction	Moderate – Benchmark dataset unclear	Moderate – Sampling not transparent	Moderate – Internal validation only	Low – Coherent findings	Moderate
[29] Classification of Lung Disease (Deep Learning)	Low – Explicit disease inclusion	Low – Large annotated dataset	Low – External validation confirms robustness	Low – Consistent synthesis	Low
[30] Voice Analysis Framework for Asthma–COVID-19	Moderate – Mixed disease inclusion	Moderate – Convenience sampling	Moderate – Limited validation	Low – Logical outcome interpretation	Moderate
[31] Advanced Ensemble Learning for Asthma Prediction	Low – Retrospective inclusion transparent	Low – Clearly defined patient data	Low – Split and cross-validation robust	Low – Interpretation evidence-based	Low
[32] MeLoDicA: Audio-Based Asthma Detection	Moderate – Dataset partially described	Moderate – No sampling frame	Moderate – Small dataset, cross-validation only	Moderate – Plausible but limited generalization	Moderate
[33] AI Sound Recognition on Medication Adherence	Low – Benchmark data inclusion explicit	Low – Public dataset benchmark	Low – Transparent validation	Low – Conclusions well supported	Low