

# ARTIFICIAL INTELLIGENCE APPLICATIONS IN DIAGNOSIS, PREDICTION, AND CLINICAL DECISION SUPPORT FOR CHEST DISEASES: A SYSTEMATIC REVIEW

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## Abstract

**Background:** Artificial intelligence (AI) and machine learning (ML) are increasingly applied in respiratory medicine for diagnosis, prognosis, and clinical decision support. Despite promising results, clinical adoption is limited due to methodological, validation, and integration challenges. We aimed to systematically review peer-reviewed studies on AI/ML applications in the diagnosis, screening, prediction, and decision support for chest diseases. **Methods:** This review followed PRISMA guidelines. Eligible studies, published between 2020 and 2024, included human participants with conditions such as pneumonia, asthma, lung cancer, or osteoporosis, where AI/ML algorithms were applied to imaging or clinical data. Searches were conducted in PubMed, Scopus, Web of Science, and IEEE Xplore. Two reviewers independently performed study selection, data extraction, and quality assessment. A narrative synthesis was undertaken due to heterogeneity in study populations, AI methods, and outcomes. **Results:** Nine studies involving 55,117 participants were included: five randomized controlled trials, three retrospective diagnostic or observational studies, and one secondary RCT analysis. AI/ML applications demonstrated high diagnostic accuracy, workflow efficiency, and predictive capabilities across diverse clinical contexts. Notable outcomes included: a Random Forest model achieving an AUC of 0.907 for *Pneumocystis jirovecii* pneumonia diagnosis; AI-assisted CT interpretation reducing reporting times by 22.1%; logistic regression detecting severe asthma exacerbations with 90% sensitivity; and AI-enabled chest radiography triaging increasing osteoporosis detection rates more than tenfold. Radiomics-based nomograms predicted lung cancer invasiveness and therapeutic response with AUCs >0.80. AI-based CAD improved detection of actionable lung nodules and enhanced non-radiologists' chest X-ray interpretation accuracy. **Conclusion:** AI/ML tools show significant potential to improve diagnostic accuracy, efficiency, and risk stratification in chest diseases.

However, broader clinical integration requires multicenter validation, standardized methodologies, transparency in algorithms, and evidence linking AI use to improved patient outcomes.

**Keywords:** Artificial Intelligence, Machine Learning, Chest Diseases, Diagnosis, Prediction, Clinical Decision Support, Radiomics, Deep Learning.

## INTRODUCTION

Artificial intelligence (AI) and its subset, machine learning (ML), is a transformative technology in respiratory medicine, offering new capabilities for disease detection, diagnosis, prognosis, and treatment guidance. The increasing availability of large-scale medical imaging datasets, advances in computational power, and the development of sophisticated algorithms have enabled AI applications to achieve diagnostic performances approaching or surpassing expert clinicians in certain contexts (Kaplan et al. 2021).

In lung cancer management, radiomics—quantitative extraction of imaging features from radiological scans—combined with AI has shown promise in risk prediction, early diagnosis, treatment response assessment, and prognostic evaluation (Tunali et al. 2021). These methods convert standard-of-care images into high-dimensional data that can be integrated with clinical, pathological, and genomic information to generate non-invasive biomarkers. However, variability in image acquisition, feature extraction protocols, and model validation approaches remains a challenge for broader clinical adoption (Tunali et al. 2021).

Deep learning (DL), convolutional neural networks, show strong performance in pulmonary nodule detection and segmentation, crucial for early lung cancer diagnosis (Gao et al. 2025). Automated detection systems can reduce radiologists' workload and improve diagnostic consistency, although issues such as the lack of external validation, standardization of datasets, and reproducibility continue to hinder widespread implementation (Gao et al. 2025). AI approaches have also been applied to predict clinical outcomes in patients undergoing immunotherapy or targeted therapy for lung cancer, integrating imaging-derived features with multi-omics data to identify responders and non-responders (Yin et al. 2022).

Beyond oncology, AI/ML applications are expanding in chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD) and asthma. Predictive models for COPD prognosis have been developed using both conventional ML and DL approaches, with mixed evidence regarding their superiority over established clinical risk scores (Smith et al. 2023).

AI tools are also being explored for pulmonary function test interpretation and differential diagnosis between overlapping obstructive airway diseases (Kaplan et al. 2021). In interstitial lung diseases (ILDs), AI-driven image analysis and computer-aided diagnosis systems have been investigated for both diagnostic support and prognostic modelling, leveraging CT imaging and pulmonary function data to guide multidisciplinary decision-making (Dack et al. 2023).

In infectious disease contexts, AI has been applied to tuberculosis (TB) detection and latent TB infection (LTBI) differentiation, addressing limitations of conventional diagnostic tools. ML algorithms integrating immunological, imaging, and molecular biomarkers show potential for more accurate classification between LTBI and active TB, which could

improve treatment targeting and public health control measures (Li et al. 2023). Similarly, in critical care, ML-based models for acute respiratory distress syndrome (ARDS) detection and prediction have demonstrated the capacity to analyze complex clinical and imaging data for earlier intervention (Rubulotta et al. 2024).

Despite these advancements, the translation of AI models into routine clinical practice remains limited. Key barriers include heterogeneity in datasets, insufficient multicenter validation, lack of interpretability of complex models, and regulatory and ethical considerations. This systematic review aims to synthesize current evidence on AI and ML applications in the diagnosis, prognosis, and clinical decision support for chest diseases, highlighting their clinical potential, limitations, and future research directions, with a focus on bridging methodological gaps to enable safe and effective integration into healthcare systems.

## METHODOLOGY

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A review protocol was developed in advance to define the objectives, eligibility criteria, and planned procedures for study selection, data extraction, and synthesis. The review focused on peer-reviewed studies published between 2020 and 2024 that investigated the application of artificial intelligence (AI) or machine learning (ML) in the diagnosis, screening, prediction, or clinical decision support for chest diseases. Eligible studies included human participants of any age with conditions such as pneumonia, asthma, lung cancer, or osteoporosis, in which AI or ML algorithms were applied to imaging or clinical data. Studies were required to report on diagnostic performance measures (sensitivity, specificity, AUC), workflow efficiency, clinical outcomes, or predictive accuracy, and could include randomized controlled trials (RCTs), observational studies, retrospective diagnostic studies, or secondary analyses of RCT datasets. Exclusion criteria comprised non-human studies, conference abstracts without full-text availability, reviews, editorials, letters, and studies without sufficient methodological detail or outcome data.

A literature search was conducted in PubMed, Scopus, Web of Science, and IEEE Xplore to identify relevant studies. The search strategy combined Medical Subject Headings (MeSH) and free-text terms relating to AI, ML, chest diseases, imaging modalities, and decision support systems. An example search string used in PubMed was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network") AND ("chest" OR "lung" OR "pneumonia" OR "asthma" OR "pulmonary nodule" OR "lung cancer" OR "osteoporosis") AND ("diagnosis" OR "screening" OR "prediction" OR "decision support"). In addition to database searching, reference lists of included studies and relevant reviews were screened manually to capture additional eligible articles.

Two reviewers screened the titles and abstracts of all retrieved citations. Full texts of relevant studies were assessed against the eligibility criteria, and disagreements at any stage were resolved by discussion or, if necessary, consultation with a third reviewer. The study selection process was documented in a PRISMA flow diagram. Data extraction was

carried out by two reviewers using a standardized form that captured study citation, country and setting, sample size and participant characteristics, study design, AI or ML method employed, comparator, outcome measures, main findings, and conclusions. Any discrepancies in extracted data were resolved by consensus.

Each study was evaluated independently by two reviewers, and quality assessments informed the interpretation of findings. Due to the heterogeneity in study populations, AI applications, algorithms, validation methods, and reported outcomes, a meta-analysis was not feasible. A narrative synthesis was performed, grouping results by clinical application area infectious disease diagnosis, lung cancer detection, osteoporosis screening, and asthma management, and summarizing key patterns and differences across the included studies.

## RESULTS

We include nine studies published between 2020 and 2024 and together included a total of 55,117 participants. Study designs comprised five randomized controlled trials (Yacoub et al. 2022; Lin et al. 2024; Seol et al. 2021; Nam et al. 2023; Lee et al. 2022), three retrospective diagnostic or observational studies (Li et al. 2023; Huang et al. 2022; Liu et al. 2023), and one secondary analysis of a randomized trial dataset (Zhang et al. 2020). The studies were conducted in a variety of clinical contexts, including tertiary hospitals, outpatient clinics, and community health screening centers. Populations ranged from pediatric patients with asthma to adults undergoing lung cancer screening, with sample sizes varying from 89 to 40,658 participants. Study characteristics, detailed demographic characteristics, main findings, and conclusions are summarized in Table 1 & 2.

### Main Findings

Li et al. (2023) validated four machine learning models to diagnose *Pneumocystis jirovecii* pneumonia (PCP) in patients with severe pneumonia. The Random Forest model, which include four noninvasive clinical indicators (neutrophil count, globulin,  $\beta$ -D-glucan, and ground-glass opacity), achieved the highest diagnostic performance with an AUC of 0.907, showing the potential to facilitate early diagnosis and improve prognosis.

Yacoub et al. (2022) evaluated the integration of an AI platform into chest CT interpretation workflows and found that AI assistance reduced radiologists' interpretation times by 22.1% without compromising accuracy, highlighting its potential to improve efficiency in routine practice. Zhang et al. (2020) applied machine learning algorithms to daily home monitoring data, including peak expiratory flow and symptom scores, from adults with persistent asthma. The resulting logistic regression model detected severe asthma exacerbations with 90% sensitivity and 83% specificity, indicating the feasibility of proactive exacerbation detection.

Lin et al. (2024) assessed AI-enabled analysis of chest radiographs to identify high-risk individuals for osteoporosis screening and reported that targeted dual-energy X-ray absorptiometry (DXA) in this group increased detection rates to 11.1% compared with 1.1% in controls (OR = 11.2,  $p < 0.001$ ). Seol et al. (2021) investigated the Asthma-

Guidance and Prediction System (A-GPS), an AI-assisted clinical decision support tool, and found that it reduced clinician time spent reviewing electronic health records (median 3.5 vs. 11.3 minutes), although it did not alter asthma exacerbation rates compared with usual care. Huang et al. (2022) developed a CT-based radiomic nomogram that combined nodular and perinodular radiomic features with clinical–radiological data, achieving AUCs above 0.90 in both internal and external validation cohorts for predicting pathological invasiveness in lung cancer. Liu et al. (2023) created a radiomics-clinical nomogram to predict major pathological response (MPR) to neoadjuvant immunochemotherapy in patients with non-small cell lung cancer (NSCLC), reporting AUCs of 0.84 in the training cohort and 0.81 in the validation cohort.

Nam et al. (2023) shows that AI-based computer-aided detection (CAD) in a health screening population improved the detection of actionable lung nodules from 0.25% to 0.59% (OR = 2.4,  $p = 0.008$ ) and also increased the detection of malignant nodules. Lee et al. (2022) evaluated AI-assisted chest radiograph interpretation by nonradiologist physicians and found improved diagnostic accuracy for lung lesions (AUC 0.840 vs. 0.718,  $p = 0.017$ ) and reduced false referral rates, without affecting clinical decision-making patterns.

**Table 1: Summary of Included Studies**

Citation	Sample Size	Study Population	Study Design	Study Aim	Methodology
Li et al. 2023	704	Patients with severe pneumonia who underwent bronchoalveolar lavage in West China Hospital	Retrospective study	Develop a rapid, noninvasive machine learning model for diagnosing <i>Pneumocystis jirovecii</i> pneumonia (PCP)	Collected clinical, laboratory, and imaging data from 2010–2021; identified PCP-associated factors; built and validated four ML models (LR, XGBoost, RF, LightGBM); evaluated diagnostic performance (AUC)
Yacoub et al. 2022	390	Outpatient chest CT patients (204 women, 186 men; mean age 62.8)	Prospective randomized single-center study	Assess impact of automated AI platform on radiologists' chest CT interpretation times	Randomized scans to AI-assisted or non-AI-assisted interpretation; three cardiothoracic radiologists measured interpretation time; compared times across scan categories
Zhang et al. 2020	2,010 patients (728,535 daily records)	Adults with persistent asthma from SAKURA RCT	Secondary analysis of RCT dataset	Develop ML algorithm to detect severe asthma exacerbations using home monitoring data	Used peak expiratory flow & symptom scores; applied preprocessing, PCA, and ML models (logistic regression, decision tree, Naïve Bayes, perceptron); evaluated with stratified cross-validation

Lin et al. 2024	40,658 screened; 4,912 AI high-risk participants	Adults $\geq 40$ years with chest radiography, no prior DXA	Randomized controlled trial	Evaluate DXA screening effectiveness in AI-identified high-risk patients for osteoporosis	AI model analyzed chest radiographs to flag high-risk patients; randomized to reimbursed DXA screening vs usual care; compared new-onset osteoporosis detection rates
Seol et al. 2021	184	Children ( $<18$ ) with asthma or asthma-like symptoms in Mayo Clinic primary care	Single-center pragmatic RCT with stratified randomization	Test AI-assisted clinical decision support (A-GPS) on asthma management	Quarterly A-GPS reports (summaries, ML risk prediction, management suggestions) vs usual care; measured asthma exacerbations, clinician EHR review time, costs
Huang et al. 2022	373	Patients with solitary pulmonary nodule from 3 Chinese centers	Multicenter retrospective diagnostic study	Develop CT-based radiomic nomogram to predict pathology invasiveness	Extracted radiomic features from nodular and perinodular areas; built radiomic & clinical-radiological signatures; combined into nomogram; validated internally & externally
Liu et al. 2023	89	NSCLC patients (stage IB–IIIC) undergoing neoadjuvant immunotherapy and surgery	Retrospective study with training/validation sets	Predict major pathological response (MPR) using CT-based radiomics and clinical data	Manual tumor segmentation; extracted 1,746 radiomic features; selected and combined with clinical variables into logistic regression nomogram; validated performance
Nam et al. 2023	10,476	Health screening participants receiving chest radiography	Pragmatic open-label RCT	Evaluate AI-CAD effect on detection of actionable lung nodules	Randomized to AI-assisted or non-AI-assisted interpretation; radiologists reviewed with/without AI results; confirmed findings with CT; compared detection rates
Lee et al. 2022	323	Respiratory outpatient clinic patients	Multicenter prospective randomized trial	Test AI-assisted CXR interpretation by nonradiologists	Patients randomized to AI-assisted or non-assisted interpretation; lung lesions recorded; reference standard from radiologists; compared diagnostic accuracy and clinical decisions

**Table 2: Citation, Demographics, Main Findings, and Conclusion**

Citation	Demographics	Main Findings	Conclusion
Li et al. 2023	704 patients with severe pneumonia, West China	RF model with four noninvasive indicators	Model provides accurate, rapid, and noninvasive

	Hospital, October 2010 – April 2021	(neutrophil count, globulin, $\beta$ -D-glucan, GGO) achieved AUC 0.907 for PCP diagnosis	diagnostic aid for early PCP detection and prognosis improvement
Yacoub et al. 2022	390 outpatient chest CT patients (mean age 62.8 $\pm$ 13.3, 204 women, 186 men), January 19–28, 2021	AI-assisted interpretation reduced CT reading time by 22.1% compared to non-AI	Integration of AI in workflow enhances radiologist efficiency without sacrificing accuracy
Zhang et al. 2020	2,010 adults with persistent asthma from SAKURA RCT dataset	Logistic regression model detected severe asthma exacerbations with 90% sensitivity and 83% specificity	Daily monitoring with ML can enable early detection and intervention for exacerbations
Lin et al. 2024	40,658 adults $\geq$ 40 years, chest radiography in 2022, 4,912 high-risk identified by AI	DXA screening in AI-identified high-risk group increased osteoporosis detection rate (11.1% vs 1.1%)	AI triaging via chest radiographs improves osteoporosis screening yield
Seol et al. 2021	184 children (<18) with asthma or asthma-like symptoms, Mayo Clinic primary care	A-GPS reduced clinician EHR review time but no significant change in exacerbation rates	AI-assisted CDS improve workflow efficiency without compromising patient outcomes
Huang et al. 2022	373 patients with solitary pulmonary nodules from 3 Chinese centers	Radiomic nomogram combining nodular and perinodular features with clinical data achieved AUCs of 0.94, 0.90, and 0.92 in different cohorts	Radiomic-clinical models can accurately predict invasiveness to guide surgical planning
Liu et al. 2023	89 NSCLC patients (stage IB–IIIC) receiving neoadjuvant immunochemotherapy	Radiomics-clinical nomogram predicted MPR with AUCs of 0.84 (training) and 0.81 (validation)	Nomogram offers a noninvasive tool for pre-treatment prediction of response to therapy
Nam et al. 2023	10,476 health screening participants, median age 59 years	AI-CAD increased detection of actionable lung nodules (0.59% vs 0.25%), OR 2.4	AI-CAD can enhance lung cancer screening programs' diagnostic yield
Lee et al. 2022	323 respiratory outpatient clinic patients	AI-assisted CXR improved diagnostic accuracy (AUC 0.840 vs 0.718) and reduced false referrals	AI support improves nonradiologists' diagnostic performance without changing clinical decision patterns

## DISCUSSION

### Comparison with Previous Studies

The findings from the nine included studies in this review show that artificial intelligence (AI) and machine learning (ML) methods have good accuracy in the diagnosis, prediction, and clinical decision support for chest diseases. This aligns with evidence from broader literature. For example, de Margerie-Mellon et al. (2022) reported that convolutional neural network-based systems for lung nodule detection and classification on CT images now reach or surpass radiologist performance in some tasks, particularly in lung cancer screening workflows.

Huang et al. (2023) emphasized the value of AI in early lung cancer diagnosis and prognosis, with natural language processing, ML, and deep learning demonstrating excellent diagnostic accuracy across multiple settings. These parallels support the robustness of our findings in both infectious and oncologic domains.

Our results also echo Adams et al. (2023), who noted that AI/ML tools can improve lung cancer screening efficiency, from eligibility determination to nodule classification, while also enabling opportunistic screening for other conditions. Several included studies in this review demonstrated similar benefits, such as improved detection rates and reduced interpretation time in screening contexts.

In infectious disease applications, Peiffer-Smadja et al. (2019) and Theodosiou et al. (2023) observed that ML-based clinical decision support systems (ML-CDSS) offer promising diagnostic and prognostic capabilities, particularly in sepsis prediction, antimicrobial prescribing, and imaging-based detection of pulmonary tuberculosis. These insights reinforce the utility of AI in respiratory infection diagnosis, as reflected in the included studies that targeted pneumonia and tuberculosis detection.

### Clinical Implications

The potential of AI to augment clinician performance is a consistent theme across our findings and the supporting literature. De Margerie-Mellon et al. (2022) highlighted how AI can non-invasively characterize tumors, predict histological subtypes, and even estimate prognosis. Our included studies demonstrate similar predictive capabilities, such as radiomics-based models for treatment response and risk stratification.

Adams et al. (2023) underscore that such tools address health equity gaps by extending specialist-level diagnostic support to under-resourced settings—an implication mirrored in our review's findings that AI can assist non-radiologist physicians in achieving comparable diagnostic accuracy.

Theodosiou et al. (2023) and Peiffer-Smadja et al. (2019) point to AI's role in accelerating laboratory workflows, predicting antibiotic resistance, and integrating clinical imaging into decision support systems. The overlap with our findings suggests that AI deployment in chest disease contexts could also facilitate earlier treatment initiation and optimized antimicrobial stewardship.

### Limitations and Challenges

While performance metrics are encouraging, both our review show persistent challenges to clinical translation. A major barrier is limited generalizability due to single-center

datasets and high-income country bias (Peiffer-Smadja et al. 2019; de Margerie-Mellon et al. 2022). Lack of algorithm transparency also undermines clinician trust, as noted by Theodosiou et al. (2023). Huang et al. (2023) found that despite high diagnostic accuracy in controlled studies, real-world clinical integration remains minimal, with few prospective, multicenter validations available. Adams et al. (2023) found a gaps in evidence linking AI use to improved patient outcomes.

## CONCLUSION

This systematic review show that artificial intelligence and machine learning applications offer a potential in improving the diagnosis, prognosis, and clinical decision support for a wide range of chest diseases, including infectious, obstructive, oncologic, and metabolic conditions. In clinical settings, these tools have shown the ability to enhance diagnostic accuracy, increase screening yields, improve workflow efficiency, and support risk stratification. Despite strong performance metrics in controlled studies, widespread clinical adoption remains limited due to challenges in external validation, dataset heterogeneity, algorithm transparency, and integration into existing healthcare systems.

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