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AI and Innovation in Pulmonology: How Technology is Changing Lung Care

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Abstract—This paper provides a comprehensive review of artificial intelligence (AI) applications in pulmonology, the branch of medicine dedicated to the diagnosis and treatment of diseases affecting the respiratory system. Lung diseases—including chronic obstructive pulmonary disease (COPD), lung cancer, asthma, interstitial lung disease, and obstructive sleep apnea—collectively constitute one of the most significant contributors to global morbidity and mortality. Despite advances in diagnostic technology, a large proportion of these conditions are identified only at an advanced stage when therapeutic options are substantially limited. AI techniques, encompassing supervised machine learning, convolutional neural networks (CNNs), recurrent architectures, and large language models (LLMs), have demonstrated substantial promise in addressing these diagnostic and management gaps. This paper systematically reviews peer-reviewed literature published between 2019 and 2025 and examines AI contributions across six major clinical domains: lung imaging (CT and chest X-ray), pulmonary function testing (spirometry), bronchoscopic procedures, COPD management, sleep medicine, and predictive analytics. Critical challenges that must be resolved before widespread clinical deployment are also addressed, including model explainability, dataset bias, regulatory frameworks, and the ethical principles governing human–AI collaboration in healthcare.

Index Terms—Artificial intelligence, pulmonology, deep learning, COPD, lung cancer, spirometry, bronchoscopy, sleep apnea, clinical decision support, explainable AI.

I. INTRODUCTION

Lung diseases represent one of the most significant global health burdens of the twenty-first century. Conditions such as chronic obstructive pulmonary disease (COPD), lung cancer, asthma, and obstructive sleep apnea affect hundreds of millions of individuals across all age groups and geographic regions. Despite the availability of effective treatments, these conditions are frequently diagnosed at an advanced stage, primarily because early symptoms are non-specific and are often attributed to ageing or lifestyle factors. This diagnostic delay substantially worsens prognosis and increases the long-term cost of care [1].

The global demand for specialist pulmonologists continues to outpace supply, particularly in low- and middle-income countries. In many regions, patients may wait months for a specialist appointment, and access to diagnostic equipment such as high-resolution CT scanners or full polysomnography facilities remains limited. These systemic constraints make it unlikely that workforce expansion alone will close the diagnostic gap [2].

Artificial intelligence (AI) refers to the branch of computer science concerned with building systems that can learn from data, identify patterns, and make predictions or decisions without explicit programming. Within healthcare, AI encompasses a spectrum of approaches: rule-based expert systems, classical machine learning algorithms such as random forests and support vector machines, and deep learning architectures including CNNs, recurrent neural networks (RNNs), and transformer-based models [2].Computer-aided diagnosis in medicine dates from the 1970s, but the current generation of AI tools is fundamentally different: trained on millions of clinical examples, they generalize across diverse patient populations and in several domains have demonstrated accuracy comparable or superior to that of trained specialists [1, 3].In pulmonology specifically, AI has demonstrated the ability to detect lung nodules with near-perfect sensitivity from CT images, interpret spirometry at a level exceeding board-certified pulmonologists, guide bronchoscopic procedures using three-dimensional airway reconstructions, predict acute COPD exacerbations using sensor-equipped inhalers, and screen for sleep apnea risk using simple clinical variables [4, 8, 9]. This paper provides a structured review of these capabilities and the challenges that remain.

II. BACKGROUND

The history of AI in medicine spans three broad phases. The first phase (1970s–1990s) was characterized by rule-based expert systems that encoded clinical knowledge as explicit if-then rules. These systems demonstrated proof-of-concept but were brittle and difficult to maintain as medical knowledge evolved [2].

The second phase (1990s–2010s) saw the rise of classical machine learning. Algorithms such as decision trees, random forests, and support vector machines were trained on structured clinical data—laboratory values, vital signs, spirometry indices—and produced useful predictive models. However, they struggled with high-dimensional unstructured data such as medical images [2].

The third and current phase is defined by deep learning. CNNs are now the standard architecture for medical image analysis including chest CT, X-ray, and pathology slides. Transformer-based models have advanced the processing of sequential clinical data such as respiratory waveforms and electronic health records. The availability of large CT scan repositories, national spirometry databases, and multicenter polysomnography archives has provided the training substrate required for clinically relevant AI in pulmonology [3, 5].

III. LITERATURE REVIEW

Table I summarizes 10 representative studies on AI applications in pulmonology, selected to span distinct clinical domains and illustrate a range of methodologies and reported outcomes. Studies are drawn from peer-reviewed journals and limited to work published between 2019 and 2025.

TABLE I. SUMMARY OF KEY STUDIES ON AI IN PULMONOLOGY (2019–2025)

Ref	Authors	Year	Topic / Focus	Key Finding
[1]	Topalovic et al.	2019	AI vs. pulmonologists in spirometry	AI outperformed board-certified pulmonologists in reading pulmonary function tests.
[2]	Karthika et al.	2024	AI across all respiratory care domains	Promising results in lung function testing, sleep medicine, and bronchoscopy.
[3]	MDPI Sys. Review	2025	Deep learning for CT-based lung cancer detection	Sensitivity 95–99%; classification accuracy 99.6% across 80 studies.
[4]	Brower, Sengupta et al.	2025	AI in interventional pulmonology / bronchoscopy	AI improves planning and real-time guidance for endobronchial procedures.
[5]	Nair, Devi & Bhasi	2024	Lung cancer detection via neural networks + random forest	99.6% sensitivity and 94.7% specificity on CT scan datasets.
[6]	Springer Sys. Review	2024	Deep learning vs. radiologists in lung cancer CT	AI showed higher specificity than expert radiologists, reducing false positives.
[7]	Wang et al.	2022	Deep learning for spirometry quality assurance	AI reliably assessed technical quality of spirometry maneuvers before interpretation.
[8]	Snyder, DePietro et al.	2025	COPD exacerbation prediction via smart inhalers	ML model predicted acute COPD episodes in advance using sensor-integrated inhalers.
[9]	Mosteiro-Añón et al.	2025	AI-based early screening for sleep apnea	AI predicted OSA risk from clinical/demographic data before polysomnography.
[10]	Gompelmann et al.	2025	AI for interstitial lung disease via lung function	AI diagnosed ILD from lung function data at accuracy comparable to specialists.

The studies collectively demonstrate consistent performance gains across multiple pulmonological domains. Detection-focused models—lung nodule identification and sleep apnea screening—report the strongest quantitative outcomes, while management-focused applications such as COPD exacerbation prediction and digital inhaler monitoring represent an emerging and clinically impactful area [5, 8].

IV. AI IN LUNG IMAGING

A. Automated Detection of Lung Nodules: CT scanning is the primary imaging modality for evaluating the lungs. Reading a chest CT study is time-consuming: a thoracic CT may contain several hundred axial slices and radiologists must systematically examine each for subtle abnormalities. AI systems trained on large CT datasets have been developed to automate the detection, segmentation, and classification of pulmonary nodules [3].

A systematic review of 80 studies reported detection sensitivity of 95–99%, tumor segmentation accuracy of 97%, and malignancy classification accuracy of 99.6% [3]. The InceptionResNetV2 architecture achieved a nodule detection rate of 98.5%, while the UNet segmentation model achieved a Jaccard index of 95.3% for tumor boundary delineation [6]. More recent architectures such as YOLOv11 frame nodule detection as a real-time object detection problem, enabling simultaneous localization and classification within a single forward pass [3].

B. AI vs. Radiologists;A 2024 systematic review in European Radiology compared AI and expert radiologists across 20 studies in lung cancer diagnosis from CT [6]. AI was comparable to radiologists in sensitivity and demonstrated higher specificity in several studies—reducing the number of patients referred for unnecessary biopsy. These findings support a role for AI as a second reader in routine CT reporting workflows [6].

C. Chest X-Ray Analysis: Chest radiography is the most widely performed imaging investigation worldwide. AI systems detect consolidation, pleural effusion, cardiomegaly, pneumothorax, and interstitial changes. In the pulmonology context, AI-based X-ray analysis has potential utility as a first-line screening tool in primary care or resource-limited settings where CT is not available [2].

D. Explainability in AI Imaging: A recognized limitation of deep learning models is opacity—commonly referred to as the black box problem. Techniques such as Grad-CAM generate saliency maps highlighting the spatial regions most influential to the model's classification decision. One study reported that a CNN augmented with Grad-CAM achieved 97.78% classification accuracy, with saliency maps consistently highlighting anatomically plausible regions [5]. SHAP values and LIME offer complementary approaches for structured data, attributing each input feature a numerical contribution to the model output [5].

V. AI IN PULMONARY FUNCTION TESTING

Spirometry is the cornerstone diagnostic test for obstructive and restrictive lung diseases, measuring forced vital capacity (FVC), forced expiratory volume in one second (FEV1), the FEV1/FVC ratio, and the shape of the flow-volume curve. Errors in interpretation are common in non-specialist settings and contribute significantly to under- and over-diagnosis of COPD and asthma globally [1].

Topalovic et al. (2019) demonstrated that an AI system trained on a large dataset of spirometry records could interpret pulmonary function tests with accuracy exceeding that of board-certified pulmonologists [1]. The model identified subtle features in the flow-volume curve associated with specific diagnoses that may not be consistently recognized through visual inspection alone. Quality assurance of spirometry efforts presents a separate challenge. Wang et al. (2022) developed a deep learning model capable of automatically assessing spirometry quality from both numerical indices and curve shape, enabling automated rejection of technically substandard tests before clinical interpretation [7]. A 2025 study in Thorax demonstrated that AI analysis of lung function data could correctly diagnose interstitial lung disease with accuracy closely comparable to specialist clinicians [10].

VI. AI IN BRONCHOSCOPY

A. Navigational Guidance: Bronchoscopy involves the insertion of a flexible endoscope into the tracheobronchial tree for direct visualization and tissue sampling. Reaching peripheral lesions requires advanced navigational techniques. Electromagnetic navigation bronchoscopy (ENB) systems create a virtual roadmap of the airway tree from pre-procedure CT data and track the bronchoscope in real time. AI enhancement improves the accuracy of the CT-based airway map and predicts the optimal pathway to the target lesion [4].

B. Endobronchial Ultrasound (EBUS) EBUS-TBNA is the standard of care for staging non-small cell lung cancer. AI models trained on annotated EBUS datasets assist clinicians in identifying optimal sampling sites and provide an objective assessment of lymph node characteristics. Early results suggest that AI-assisted EBUS guidance could reduce sampling inadequacy rates and improve staging accuracy, particularly for less experienced operators [4].

C. Rapid On-Site Evaluation (ROSE) ROSE involves immediate cytopathological assessment of bronchoscopy specimens at the bedside. A deep learning model developed to assist with ROSE classification achieved an AUC of 0.9846 in distinguishing malignant from non-malignant cytology specimens [2]. This suggests AI could provide a practical substitute for on-site pathological expertise in resource-limited settings.

D. Training and Simulation: AI has potential applications in bronchoscopy training. Simulation platforms that use AI to evaluate trainee technique—scoring scope handling, time to target, mucosal trauma, and procedure efficiency—could accelerate skill acquisition and provide objective competency benchmarks [4].

VII. AI IN COPD MANAGEMENT

A. Detection and Severity Quantification: COPD is characterized by persistent airflow limitation resulting from airway inflammation and structural remodeling of the lung parenchyma. It is the third leading cause of death worldwide. COPD is highly phenotypically heterogeneous: patients with similar FEV1 values may have very different patterns of lung destruction, symptom burden, and disease progression. AI models applied to CT imaging quantify structural features not captured by spirometry, including emphysema extent, airway wall thickness, and air trapping, enabling more precise phenotyping and individualized treatment selection [5].

B. Exacerbation Prediction: Acute exacerbations of COPD are the primary driver of hospitalization and a major determinant of disease progression and mortality. Snyder et al. (2025) developed a machine learning model that used data from a sensor-integrated inhaler—inhaler actuation frequency, inhalation flow rate, and acoustic features—to predict the probability of an acute COPD episode in the days preceding its onset [8]. The model demonstrated clinically meaningful predictive accuracy in a prospective validation cohort.

C. Smart Inhalers and Digital Monitoring: Sensor-equipped inhalers record medication activations, measure inhalation technique parameters, and transmit data to connected health platforms. AI algorithms generate adherence reports, identify technique errors, detect patterns preceding exacerbations, and enable clinicians to monitor patients between visits. Studies of smart inhaler programs in COPD have demonstrated improvements in medication adherence and reductions in exacerbation frequency in randomized controlled trials [8].

VIII. AI IN SLEEP MEDICINE

Obstructive sleep apnea (OSA) is the most common sleep disorder, estimated to affect approximately one billion individuals worldwide. Undiagnosed OSA is associated with increased risk of cardiovascular disease, metabolic syndrome, neurocognitive impairment, and road traffic accidents. The standard diagnostic test—attended in-laboratory polysomnography—is expensive and has limited availability in most health systems [9].

Mosteiro-Añón et al. (2025) demonstrated that a machine learning-based clinical decision support tool could accurately predict OSA risk using readily available clinical and demographic variables—including age, BMI, neck circumference, presence of hypertension, and daytime sleepiness scores—before formal sleep testing [9]. This risk-stratification approach enables selective referral for polysomnography and substantially reduces unnecessary overnight testing.

AI has also been integrated into auto-titrating CPAP (APAP) devices, which continuously adjust therapeutic pressure in response to detected apneas and flow limitations, optimizing treatment throughout the night [2]. Compliance data collected by CPAP devices is analyzed to identify patterns associated with therapy abandonment, enabling targeted support interventions. A review of AI-based acoustic lung sound analysis reported sensitivity of approximately 80% and specificity of 85% for detecting abnormal respiratory sounds, with more recent models exceeding 97% accuracy [2, 5].

IX. PREDICTIVE ANALYTICS AND PERSONALIZED CARE

Predictive analytics in pulmonology integrates heterogeneous clinical data—imaging findings, pulmonary function test results, laboratory biomarkers, genomic data, wearable device recordings, and longitudinal electronic health records—to estimate individual patient risk of disease onset, exacerbation, or progression. Clinical decision support systems (CDSS) incorporating AI predictive models have been developed for asthma, COPD, and pulmonary hypertension, generating real-time alerts when patients are identified as high-risk [2, 5].

Large language models (LLMs) are an increasingly prominent development in clinical AI. In the pulmonology context, LLMs have been explored for automated summarization of clinical notes, extraction of structured diagnoses from unstructured discharge summaries, and generation of preliminary radiology report drafts. Research applications include automated synthesis of scientific literature to identify potential drug targets for idiopathic pulmonary fibrosis and pulmonary arterial hypertension [5].

Multimodal AI models that simultaneously process imaging data, structured clinical variables, genomic profiles, and wearable sensor outputs represent the next frontier in personalized pulmonology. Early studies combining CT-derived emphysema quantification with spirometry data and biomarker profiles have demonstrated improved prediction of COPD exacerbation risk compared to single-modality models [3, 5].

X. CHALLENGES AND ETHICAL ISSUES

A. Model Explainability: Many high-performing deep learning models do not provide human-interpretable justifications for their outputs. Post-hoc methods such as SHAP values, LIME, and Grad-CAM partially address this limitation by attributing predictions to input features or image regions. However, these methods describe model behavior at a particular input but do not guarantee faithful representation of the model's general reasoning. There is broad consensus that AI tools intended for clinical deployment should be inherently interpretable, or at minimum accompanied by rigorously validated explainability frameworks [5].

B. Regulatory Frameworks: Regulatory oversight of AI-based medical devices is still evolving. The U.S. FDA published its AI/ML-Based Software as a Medical Device (SaMD) Action Plan in 2021, and the European Medicines Agency issued revised guidance in 2023. These frameworks mandate rigorous pre-market validation studies, transparent reporting of training data characteristics, and ongoing monitoring of deployed models to detect performance degradation—model drift—over time.

C. Dataset Bias and Generalizability: Most AI models in pulmonology have been developed using retrospective datasets from large academic medical centers in high-income countries. This introduces systematic biases that may compromise model performance when applied to underrepresented demographic groups—racial and ethnic minorities, elderly populations, and patients in low-resource clinical environments where equipment calibration and data quality standards may differ [5]. A biased AI tool deployed without adequate validation in a new patient population could produce systematically inaccurate results for specific subgroups.

D. Data Privacy and Security: Developing clinical AI models requires access to large volumes of sensitive patient data. Ensuring compliance with HIPAA in the United States and GDPR in Europe while enabling the data sharing required for model development and multicenter validation is a significant technical challenge. Federated learning—in which model training is distributed across institutions without raw patient data leaving each site—and differential privacy techniques represent promising approaches for privacy-preserving AI development [5]. ***E. Human Oversight and Accountability:*** There is consistent agreement across clinical professional bodies and regulatory agencies that AI systems in healthcare should augment, not replace, clinical judgment. In legal and ethical frameworks, accountability for clinical decisions remains with the treating clinician, not the AI system. AI recommendations must be presented in a way that supports informed clinical review, including information about the model's confidence, known limitations, and the range of cases for which its performance has been validated [1, 5].

XI. FUTURE RESEARCH DIRECTIONS

Several priority areas emerge from the reviewed literature as necessary before AI applications in pulmonology can be safely and equitably deployed.

First, prospective multicenter validation is the most urgent methodological priority. The majority of published AI studies are retrospective and single-center. Prospective evaluation in diverse patient populations across multiple institutions—with pre-specified endpoints, blinded outcome assessment, and transparent subgroup performance reporting—is required before any model can be considered clinically validated [1, 5].

Second, explainability should be a first-order design requirement. Future model development should prioritize architectures that are inherently interpretable where possible, and should apply rigorous evaluation of explainability methods to confirm that they faithfully represent the model's internal reasoning [5].

Third, active diversification of training datasets is required to address demographic and geographic biases. This requires coordinated data-sharing infrastructure, standardized annotation protocols, and regulatory incentives that reward diverse validation [5].

Fourth, multimodal integration—combining CT-derived quantitative imaging biomarkers, spirometric data, serum biomarkers, genomic profiles, and wearable sensor outputs within a unified predictive model—has the potential to substantially improve diagnostic and predictive accuracy [3, 5].

Fifth, dedicated implementation science research is needed to understand how clinicians interact with AI recommendations in practice and what organizational and training conditions support safe and effective use [1]. Patient perspectives on data sharing, algorithmic transparency, and the appropriate scope of AI decision support should also be systematically incorporated into program design [5].

XII. CONCLUSION

Artificial intelligence is demonstrating clinically meaningful capabilities across the breadth of pulmonology—from near-perfect sensitivity in CT-based lung nodule detection, to AI systems that outperform specialist physicians in spirometry interpretation, to machine learning models that predict acute COPD exacerbations before clinical deterioration occurs, to AI screening tools that identify sleep apnea risk without requiring overnight polysomnography [1, 3, 8, 9]. The convergence of large clinical datasets, advances in deep learning architectures, and growing computational infrastructure has created conditions in which AI is transitioning from a research tool to a practical component of clinical care. Published models have been predominantly validated in retrospective, single-center studies using data that may not represent the full diversity of patient populations in which these tools will eventually be deployed. Model performance can degrade over time and across settings, and the opacity of deep learning models creates accountability challenges not yet fully resolved by available explainability techniques [5].The appropriate response is a structured, evidence-driven approach to implementation: prioritizing prospective multicenter validation, building explainability into model design from the outset, actively addressing dataset biases, and ensuring that AI deployment enhances rather than undermines the therapeutic relationship between clinician and patient. The goal of AI in lung medicine is to make the best standard of pulmonological care accessible to a broader population—including the millions of patients in underserved regions who currently have no access to specialist lung care. Under these principles, AI has the potential to substantially reduce the global burden of lung disease.

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