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Artificial Intelligence in Respiratory Care: An Educational Review

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Review

Artificial Intelligence in Respiratory Care: An Educational Review

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Abstract
Respiratory diseases such as chronic obstructive pulmonary disease (COPD), asthma, tuberculosis, and acute respiratory distress syndrome (ARDS) remain leading causes of morbidity and mortality worldwide. Traditional respiratory care faces challenges in early diagnosis, personalized treatment, efficient resource allocation, and optimal mechanical ventilation management. Artificial intelligence (AI) has emerged as a transformative tool, offering applications in diagnosis, monitoring, treatment optimization, critical care support, and automated ventilator control. This comprehensive review examines AI's role across the respiratory care continuum, from diagnostic imaging and spirometry interpretation to autonomous multiparameter ventilator adjustment during maintenance and weaning phases. The article highlights quantitative evidence of clinical impact, regulatory status, challenges including algorithmic bias and health equity concerns, implementation strategies, and detailed analysis of AI-driven mechanical ventilation systems. Case studies illustrate real-world outcomes with specific effect sizes. The discussion emphasizes both the promise and limitations of AI, preparing healthcare professionals and students to critically evaluate its role in clinical practice.

Keywords: artificial intelligence; respiratory care; machine learning; COPD; ventilator management; predictive analytics; ethics; precision medicine; clinical integration; algorithmic bias; health equity; closed-loop ventilation; weaning protocols

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Learning Objectives

By the end of this article, learners should be able to:

- Describe the global burden of respiratory diseases and the rationale for AI adoption across diagnostic, monitoring, and therapeutic domains

- Explain how AI technologies are applied in respiratory care, including diagnosis, monitoring, treatment, and mechanical ventilation, with specific examples of FDA-cleared tools

- Identify quantitative evidence of clinical benefits and limitations of AI integration in clinical workflows, including specific effect sizes from clinical trials

- Evaluate algorithmic bias, health equity concerns, and patient safety risks associated with AI deployment

- Discuss case studies where AI improved patient outcomes in COPD management, ventilator weaning, and critical care

- Understand AI-driven closed-loop ventilation systems, including reinforcement learning controllers, digital lung twins, and automated weaning protocols

- Recognize regulatory frameworks, implementation barriers, and best practices for AI adoption in respiratory medicine

- Appreciate future directions for AI in respiratory medicine, including personalized therapy, genomic integration, and global equity considerations

1. Introduction

Respiratory diseases are among the most prevalent health conditions worldwide. COPD alone affects over 300 million people and is projected to become the third leading cause of death globally.[1] Asthma, pneumonia, tuberculosis, and ARDS further contribute to the burden, particularly in low- and middle-income countries. Traditional respiratory care relies on clinical expertise, imaging, and pulmonary function testing, but these methods often face limitations in accuracy, timeliness, and scalability.

Mechanical ventilation, while lifesaving, presents additional challenges including ventilator-induced lung injury (VILI), patient-ventilator asynchrony, and prolonged dependence. VILI contributes to mortality rates of up to 30% in ARDS patients when tidal volumes exceed 10 mL/kg.[2] Patient-ventilator asynchrony occurs in 25–50% of ventilated patients, prolonging ventilation by 2–3 days.[3] Manual ventilator adjustment is limited by clinician workload, cognitive overload, and inter-clinician variability.

AI technologies—including machine learning (ML), deep learning (DL), natural language processing (NLP), and reinforcement learning (RL)—offer new opportunities to enhance respiratory care. By analyzing large datasets and providing continuous real-time optimization, AI can detect subtle patterns, predict disease progression, support personalized treatment, and automate complex ventilator management.[4][5][6][7][8] The integration of AI into respiratory medicine represents a paradigm shift toward precision healthcare, though adoption remains limited across most domains despite substantial potential impact on quality improvement, patient safety, patient experience, and access to care.[9]

2. Applications of AI in Respiratory Diagnosis and Monitoring

2.1. Diagnosis and Monitoring

AI algorithms analyze chest imaging, spirometry, and wearable sensor data to detect early signs of respiratory disease. Convolutional neural networks (CNNs) can identify pneumonia or tuberculosis from chest X-rays with accuracy comparable to radiologists.[4][7][8] As of early 2023, there were **42 FDA-approved AI-based software devices** specifically for thoracic radiology, primarily for pulmonary nodule detection, endotracheal tube placement monitoring, detection of emergent findings, and assessment of pulmonary parenchyma.[10] AI also supports continuous monitoring of patients with chronic conditions, alerting clinicians to early signs of deterioration.[4][5][6]

2.2. Imaging and Radiology

Radiology is a major area of AI application. Deep learning models enhance detection of lung nodules, interstitial lung disease, and COVID-19-related abnormalities.[4][7][10] AI reduces diagnostic variability and speeds up interpretation, particularly in resource-limited settings where radiologists are scarce. A comparative analysis identified 222 AI/ML-based medical devices approved in the USA and 240 in Europe between 2015 and 2020, with radiology dominating and most devices classified as low- or moderate-risk.[11] However, it is critical to note that **98% of 790 new devices** in pulmonary, sleep, and critical care medicine cleared between 2014 and 2024 used the 510(k) pathway, indicating approval based on equivalence to existing devices rather than direct evidence of improved clinical outcomes.[12]

2.3. Pulmonary Function Testing

Spirometry is a cornerstone of respiratory diagnosis, but interpretation errors are common. AI models improve accuracy by analyzing flow-volume curves and integrating patient demographics.[4][7][8] Algorithms detect technical errors and classify spirometric patterns, with some claiming to outperform pulmonologists, though rigorous multicenter validation is essential for trust and adoption.[4] This reduces misdiagnosis and supports personalized treatment plans.

2.4. Wearable Devices and Remote Monitoring

AI-powered wearables track respiratory rate, oxygen saturation, and activity levels. These devices enable continuous monitoring of patients with COPD or asthma, allowing early intervention when exacerbations are detected.[4][5][6] Connected devices integrated with environmental data help forecast asthma and COPD exacerbations, while telehealth and predictive models enable earlier, more personalized interventions.[4][5] Remote monitoring reduces hospital visits and empowers patients to manage their conditions. A systematic review and meta-analysis of 35 RCTs found that most digital health interventions involving real-time monitoring or teleconsultations for asthma and COPD were cost-effective or less expensive than standard care, with incremental cost-effectiveness ratios ranging from **€3,530.93/QALY to €286,369.28/QALY**.[13]

3. AI in Mechanical Ventilation: Maintenance and Weaning

3.1. The Challenge of Conventional Ventilator Management

Conventional ventilator management relies on intermittent human assessment, whereas AI systems provide continuous optimization using high-frequency physiologic input. Modern RL-based controllers can propose tidal volume, PEEP, FiO_2, and pressure-support changes to minimize VILI while preserving respiratory muscle activity.[14][15] Unlike manual adjustments, which are intermittent and often subject to cognitive overload, AI systems evaluate thousands of data points per minute.[14]

3.2. Closed-Loop Ventilation Systems

AI-assisted mechanical ventilation provides continuous, automated interpretation of lung compliance, resistance, gas-exchange metrics, airway pressures, and respiratory drive signals.[16] Digital lung-twin models simulate recruitment, overdistension, and derecruitment patterns, allowing adaptive PEEP strategies tailored to the patient's lung morphology.[14] Studies demonstrate improved synchrony and shortened weaning times when AI is used adjunctively with clinician oversight.[17][18]

SmartCare/PS and Adaptive Support Ventilation (ASV) are early examples of autonomous systems.[16] IntelliVent-ASV represents a more advanced closed-loop system. A prospective crossover study of IntelliVent-ASV in 85 ICU patients showed improved oxygenation and reduced variability compared to manual settings.[19] Automated systems reduced **hypoxemia episodes by 40%** and **hypercapnia events by 35%**.[19] A systematic review demonstrated that IntelliVent-ASV maintained consistent adherence to protective ventilation, keeping tidal volumes 8 mL/kg in **>95% of cases**, thereby reducing the incidence of VILI compared to conventional ventilation.[20]

More advanced systems integrate ultrasound, bioacoustic signals, esophageal pressure monitoring, and proportional assist indicators.[14] Machine learning models achieved **>90% sensitivity** in detecting patient-ventilator asynchrony compared to manual waveform inspection.[21]

3.3. AI in Ventilator Weaning

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Weaning from mechanical ventilation remains a critical challenge. Each failed extubation adds approximately **5 ICU days**, costing roughly **$15,000 per patient**.[22] AI-based prediction models have improved extubation success rates from approximately **70% (traditional indices) to >85%**.[23] AI models achieved AUC scores of **0.87–0.92** in predicting weaning readiness, outperforming the Rapid Shallow Breathing Index (RSBI) which typically achieves AUC ~0.65.[23]

A retrospective study evaluating AI integration into weaning protocols in medical and COVID-19 ICUs found that in the COVID-19 ICU, the AI-assisted intervention group (n=88) had a mean ventilation time of **244.2 hours versus 426.0 hours** in the control group (P=0.011), ICU length of stay of **11.0 days versus 18.7 days** (P=0.001), and hospital length of stay of **23.5 days versus 40.4 days** (P0.001).[24] These reductions represent a **42.6% reduction in ventilation time**, **41.2% reduction in ICU stay**, and **41.8% reduction in hospital stay**.[24]

A two-stage AI prediction system tailored weaning timing, reducing reintubation rates from **18% to 10%**.[25] AI-guided reduction in PEEP levels improved weaning success rates by **15%** compared to clinician-led protocols.[26] Across 12 trials, AI-driven ventilation reduced ICU stay by **1.5–2.5 days on average**.[27]

3.4. Safety, Explainability, and Ethical Oversight

Ethical oversight requires transparency, explainability, and safety limits to prevent adverse ventilatory decisions.[14] AI does not replace clinician judgment but augments it through tireless pattern recognition and rapid multivariable optimization.[14] AI ventilation systems require integration of >20 physiological variables; missing data reduced accuracy by **15%**.[27] Liability remains a concern; clinicians must retain oversight despite automation.[27]

4. Evidence of Clinical Impact Across Respiratory Care

4.1. Quantitative Outcomes in COPD Management

Wang et al. developed and validated an artificial neural network (ANN) model to predict 30-day readmission risk in COPD patients across eight hospitals within a large urban health system.[28] The model, implemented via a smartphone application (Re-Admit), used four clinical variables and achieved an AUC of 0.77 with sensitivity of 0.75 and specificity of 0.67. Following implementation of a targeted clinical care plan for high-risk patients, the study reported a statistically significant **48% reduction in 30-day readmission rates** in the high-risk subgroup.[28] This represents one of the few studies demonstrating a direct, quantifiable improvement in a patient-centered outcome attributable to an AI intervention in respiratory care.

4.2. Pulmonary Rehabilitation Outcomes

A systematic review and meta-analysis pooled three RCTs (456 participants) comparing AI-assisted pulmonary rehabilitation to standard care in chronic respiratory diseases, demonstrating a statistically significant improvement in 6-minute walk distance (mean difference: **22.08 meters**; 95% CI: 4.96–39.20; p=0.01).[29] While this is a validated functional outcome, the number of included studies is small, and data on long-term quality of life or survival were not reported.

4.3. Diagnostic Accuracy and Clinician Performance

A randomized clinical vignette survey study directly measured the impact of AI on diagnostic accuracy for acute respiratory failure.[30] The study demonstrated that while standard AI models improved diagnostic accuracy, **systematically biased models decreased physician performance**, and providing AI explanations did not mitigate this harm.[30] Notably, a majority of clinicians were unaware that AI models could be systematically biased.[30] This highlights critical patient safety concerns regarding automation bias and over-reliance on AI predictions.

4.4. Comparative Effectiveness Evidence

A systematic review by Lam et al. found that in 77% of 39 RCTs across specialties, AI-assisted interventions outperformed usual care, with clinically relevant outcomes improving in 70% of those studies.[31] However, most trials were small and single-center, and only a minority directly addressed respiratory conditions. A randomized clinical trial at the Mayo Clinic evaluated an AI-assisted clinical decision support tool for childhood asthma management and found no significant difference in asthma exacerbation frequency between AI and standard care groups (12% vs. 15%; OR 0.82; 95% CI 0.374–1.96; P=0.626), though the AI intervention significantly reduced clinician EHR review time (median 3.5 minutes vs. 11.3 minutes; P0.001).[32]

4.5. Limitations of Current Evidence

Systematic reviews of AI in ARDS report high model performance (AUC 0.8–1.0) for diagnostic and prognostic tasks, but most studies are retrospective and focused on model development rather than prospective clinical impact.[33][34][35] Similarly, AI-based risk scores for community-acquired pneumonia enhance prediction accuracy but lack direct evidence of improved survival or reduced readmissions from prospective trials.[36][37] The predominance of retrospective, single-center studies, the paucity of prospective multicenter RCTs, and the lack of data on long-term patient outcomes such as survival and sustained quality of life represent significant limitations of the current evidence base.[4][5][35][38][39]

5. Regulatory Status and Real-World Adoption

The FDA has articulated a tailored regulatory framework for AI-enabled medical devices, including a 5-point action plan and guidance for clinical decision-support software, emphasizing a risk-based approach.[40] As of 2025, approximately 1,000 AI-enabled devices have been approved, with a focus on fostering collaboration, promoting harmonized standards, advancing regulatory approaches supporting innovation, and supporting research related to AI performance evaluation.[40] The FDA's Total Product Life Cycle approach emphasizes continuous monitoring and iterative improvement of AI-enabled devices throughout their deployment.[40]

Real-world adoption remains heterogeneous. While AI tools for chest imaging and spirometry are increasingly used, widespread adoption is contingent upon rigorous multicenter validation and real-world evidence.[4] The Global Initiative for Chronic Obstructive Lung Disease (GOLD) 2026 report acknowledges that AI and telehealth may offer improved healthcare access and outcomes for COPD patients, but notes that evidence is still emerging and that AI comes with risks and limitations requiring careful consideration before deployment.[1]

6. Algorithmic Bias and Health Equity

6.1. Evidence of Systematic Bias

State-of-the-art AI classifiers for chest X-ray pathology **consistently and selectively underdiagnose disease** in female, Black, Hispanic, and low socioeconomic status patients, with the underdiagnosis rate being particularly pronounced in intersectional subgroups such as Hispanic women.[41][42] Deep learning models for chest X-ray disease detection encode protected characteristics such as race and biological sex within their feature representations, resulting in shifted true and false positive rates across demographic groups.[43]

AI models for predicting asthma exacerbation in children performed worse for those with lower socioeconomic status, linked to incomplete EHR data in lower SES groups.[44] Bias can be introduced through the physical design of medical technologies, unrepresentative training data, and conflation of biological with social determinants of health.[45] A scoping review found that **74.7% of clinical**

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ML models evaluated for bias demonstrated bias on sociodemographic factors, with bias disproportionately affecting groups with socioeconomic disadvantage.[46]

6.2. Regulatory and Equity Frameworks

Current regulatory guidance does not consistently include equity as a core criterion and lacks mechanisms to systematically detect or prevent bias.[47] Proprietary datasets and algorithms hamper transparency and can obscure algorithmic bias, and underrepresentation of racial and ethnic minority groups in training data is rampant.[48] Realizing AI's benefits will require proactive bias detection and mitigation with **inclusive sampling, equity audits, and stratified performance reporting**.[4][47][48]

7. Patient Safety and Implementation Barriers

7.1. Automation Bias and Over-Reliance

Long-term reliance on AI may erode clinician skills, particularly for trainees and in low-prevalence contexts, citing historical failures of computer-aided diagnosis in mammography.[49] Human oversight is essential to avoid automation bias and patient harm, and ethical frameworks, bias mitigation techniques, and transparency measures must be pursued.[6] High-quality, interoperable data and explainable models are needed to enable human oversight.[4]

7.2. Organizational and Workflow Barriers

Successful AI deployment requires simultaneous attention to strategic, operational, and implementation dimensions. Organizations often fundamentally misunderstand AI deployment—treating it as a quick technological fix rather than a **multi-year transformational process**, focusing exclusively on financial returns while ignoring quality and safety benefits, and failing to recognize that AI implementation demands profound organizational change including workforce development, cultural shifts, and workflow redesign.[9]

Practical barriers include clinician training, interoperability with existing health information systems, workflow disruption, and change management.[50] Successful AI adoption requires intentional actions to effect behavioral change, including creating AI output visualizations that are easily interpretable by clinicians.[9] Many AI-based systems in critical care remain immature, particularly their lack of situational awareness and adaptability to individual patient responses. Practical issues such as digital literacy, device access, and usability for children, older adults, and other vulnerable populations also matter for applications requiring patient interaction.[4]

7.3. Adaptive AI Engagement Strategies

Effective AI use requires adaptive flexibility rather than a one-size-fits-all approach. Clinicians should dynamically shift between "**centaur**" **strategies**—where tasks are strategically divided with careful validation of AI output—and "**cyborg**" **strategies**—where human and AI work are more tightly integrated. High-stakes clinical decisions, particularly those involving unvalidated general-purpose AI tools, demand a centaur approach with rigorous human oversight and verification. Conversely, validated tools for specific purposes or lower-stakes administrative tasks may permit more integrated cyborg collaboration.

8. Case Studies

8.1. COPD Management

AI models predict exacerbations in COPD patients by analyzing wearable data and electronic health records. Implementation of an AI-driven clinical care pathway resulted in a **48% reduction in**

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30-day readmissions in high-risk patients.[28] Early interventions reduce hospitalizations and improve quality of life.

8.2. Ventilator Weaning in COVID-19

AI algorithms assist clinicians in determining optimal timing for ventilator weaning. In COVID-19 ICU patients, AI-assisted weaning reduced mean ventilation time by **181.8 hours**, ICU length of stay by **7.7 days**, and hospital length of stay by **16.9 days** compared to controls.[24] These improvements demonstrate AI's potential in crisis management and critical care optimization.

8.3. COVID-19 Respiratory Care

During the pandemic, AI tools analyzed imaging and clinical data to triage patients, optimize ventilator use, and predict outcomes.[4][24] These applications highlighted AI's potential in crisis management, though systematic reviews revealed that most prediction models had high risk of bias and lacked external validation.[35]

8.4. Tuberculosis Screening

In resource-limited settings such as South Africa, AI-enhanced imaging tools improved TB detection rates, demonstrating AI's potential to expand access to care in low-income countries.[4] However, ensuring equitable access to AI tools globally is critical to avoid widening health disparities.

8.5. Closed-Loop Ventilation in Mixed ICU Populations

The ACTiVE trial protocol evaluated IntelliVent-ASV in diverse ICU populations, demonstrating that closed-loop ventilation modes maintain lung-protective strategies and reduce VILI. AI-based multiphase frameworks in emergency departments improved ventilator availability by **20%** during respiratory disease surges.

9. Best Practices for Implementation

Successful AI integration in respiratory care requires:

Strategic Vision: Organizations must develop multi-year AI roadmaps that prioritize quality, safety, and equity alongside financial returns.[9]

Data Management: High-quality, interoperable data infrastructure is essential. Organizations often underestimate the importance of data governance, standardization, and privacy protection.[9][40]

Clinician Training: Targeted education on AI capabilities, limitations, and adaptive engagement strategies is critical to prevent automation bias and skill erosion.[49][6]

Equity Audits: Proactive bias detection through inclusive sampling, stratified performance reporting, and equity audits must be standard practice.[4][41][47][48]

Multicenter Validation: Rigorous external validation in diverse populations and clinical settings is required before widespread deployment.[4][38][39]

Human-in-the-Loop Design: AI should augment, not replace, clinicians. Explainable models and human oversight mechanisms are essential for patient safety.[4][6]

Regulatory Compliance: Adherence to FDA guidance and risk-based frameworks ensures patient safety and facilitates adoption.[40]

10. Future Directions

Personalized Therapy: AI-driven models will tailor interventions to genetic, environmental, and lifestyle factors, advancing precision medicine.[4][5][35]

Integration with Genomics: Combining AI with genomic data will identify individual risk profiles and therapeutic targets.[4][5][35]

Global Equity: Ensuring access to AI tools in low-income countries is critical to avoid widening health disparities. Federated learning and privacy-preserving approaches may enable collaborative research without data sharing.[35]

AI-Human Collaboration: AI will augment, not replace, clinicians, enhancing decision-making and patient care while preserving the clinician-patient relationship.[4][8]

Predictive Public Health: AI could forecast respiratory disease outbreaks, supporting preventive strategies at population level.[4]

Advanced Methodologies: Graph Neural Networks, Causal Inference, Federated Learning, Self-Supervised Learning, and Large Language Models promise enhanced data integration, privacy-preserving research, and autonomous decision support.[35]

Neural Control Interfaces: Early studies suggest AI systems could respond directly to neural signals of respiratory drive.[14]

Integration with EHRs: Linking ventilator AI with EHRs could enable holistic patient management, incorporating comorbidities and longitudinal data.[14]

11. Conclusion

AI in respiratory care represents a transformative shift, offering enhanced diagnosis, treatment, and patient outcomes when deployed with rigorous validation, equity audits, and human oversight. While quantitative evidence demonstrates meaningful improvements in specific applications—including a 48% reduction in COPD readmissions, 42.6% reduction in ventilation time, and significant improvements in weaning success—most studies remain retrospective and single-center. Algorithmic bias systematically underdiagnoses disease in vulnerable populations, and automation bias poses patient safety risks. Successful implementation requires multi-year organizational transformation, clinician training, interoperable data infrastructure, and adaptive engagement strategies. AI-driven closed-loop ventilation systems show particular promise in reducing VILI, improving patient-ventilator synchrony, and optimizing weaning protocols. The future of respiratory care lies in balancing technological innovation with human-centered practice, ensuring that AI's benefits are realized equitably across all patient populations.

Glossary

Artificial Intelligence (AI): Computer systems capable of performing tasks requiring human intelligence, including pattern recognition, prediction, and decision support.

Machine Learning (ML): A subset of AI that learns patterns from data without explicit programming.

Deep Learning (DL): Neural networks with multiple layers for complex data analysis, particularly effective for image and signal processing.

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Reinforcement Learning (RL): A type of machine learning where algorithms learn optimal actions through trial and error to maximize rewards.

Convolutional Neural Networks (CNNs): Deep learning models specifically designed for image analysis.

Spirometry: Test measuring lung function, including forced expiratory volume and vital capacity.

Ventilator Management: Adjusting mechanical ventilation parameters for critically ill patients to optimize oxygenation while minimizing lung injury.

Ventilator-Induced Lung Injury (VILI): Damage to lung tissue caused by mechanical ventilation, particularly from excessive tidal volumes or pressures.

Patient-Ventilator Asynchrony: Mismatch between patient respiratory effort and ventilator delivery, leading to discomfort and prolonged ventilation.

Closed-Loop Ventilation: Automated ventilator systems that continuously adjust parameters based on real-time physiologic feedback.

Digital Lung Twin: Computational model that simulates individual patient lung mechanics to guide ventilator settings.

Predictive Analytics: Forecasting health outcomes using statistical and machine learning models applied to clinical data.

Precision Medicine: Tailoring treatment to individual characteristics, including genetic, environmental, and lifestyle factors.

Electronic Health Records (EHRs): Digital records of patient health information.

Algorithmic Bias: Systematic errors in AI predictions that disproportionately affect specific demographic groups.

Automation Bias: The tendency to over-rely on automated systems and under-value contradictory information from other sources.

510(k) Pathway: FDA regulatory pathway for medical devices demonstrating substantial equivalence to existing devices.

Area Under the Curve (AUC): A measure of diagnostic test performance, ranging from 0.5 (no better

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than chance) to 1.0 (perfect discrimination).

Federated Learning: A machine learning approach that trains models across decentralized datasets without sharing raw data, preserving privacy.

Centaur Strategy: An AI engagement approach where tasks are strategically divided between human and AI, with careful validation of AI output.

Cyborg Strategy: An AI engagement approach where human and AI work are more tightly integrated.

PEEP (Positive End-Expiratory Pressure): Pressure maintained in the airways at the end of expiration to prevent alveolar collapse.

FiO_2 (Fraction of Inspired Oxygen): The concentration of oxygen in the gas mixture delivered to the patient.

Top 10 Applications of AI in Respiratory Care

Application	Description	Clinical Impact	References
Chest Imaging Analysis	Deep learning models detect pneumonia, TB, lung nodules, and COVID-19 abnormalities on chest X-rays and CT scans	42 FDA-approved thoracic radiology AI devices; accuracy comparable to radiologists	[1–3]
Spirometry Interpretation	AI algorithms detect technical errors, classify spirometric patterns, and support diagnosis of obstructive/restrictive diseases	Reduces interpretation errors; some models claim to outperform pulmonologists	[1,2,4]
COPD Exacerbation Prediction	Wearable devices and EHR data predict exacerbations, enabling early intervention	48% reduction in 30-day readmissions with AI-driven care pathway	[1,5]
Closed-Loop Ventilator Control	AI continuously adjusts PEEP, FiO_2, tidal volume, and pressure support based on real-time physiologic data	40% reduction in hypoxemia episodes; 35% reduction in hypercapnia events; >95% adherence to lung-protective ventilation	[6–9]
Ventilator Weaning Prediction	ML models predict optimal weaning timing using multiparameter physiologic data	AUC 0.87–0.92 for weaning readiness; 42.6% reduction in ventilation time; 10% vs 18% reintubation rate	[10–12]

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Asthma Management	Remote monitoring and predictive models forecast exacerbations and guide therapy adjustments	Cost-effective digital interventions (€3,531-€286,369/QALY); mixed evidence on exacerbation reduction	[13,14]
Pulmonary Nodule Detection	Automated detection and classification of lung nodules on CT scans	FDA-cleared tools improve detection rates and reduce radiologist workload	[1–3]
ARDS Risk Stratification	ML models predict ARDS development, severity, and mortality using multimodal data	High model performance (AUC 0.8-1.0); limited prospective validation	[15–17]
Tuberculosis Screening	AI-enhanced chest X-ray interpretation for TB detection in resource-limited settings	Improved detection rates in South Africa; expands access to care	[1]
Pulmonary Rehabilitation	AI-assisted exercise programs and remote monitoring for chronic respiratory diseases	22.08-meter improvement in 6-minute walk distance (meta-analysis of 3 RCTs)	[18]

Key Takeaways

Evidence-Based Benefits: AI demonstrates quantifiable improvements in specific applications, including 48% reduction in COPD readmissions, 42.6% reduction in ventilation time, and 40% reduction in hypoxemia episodes, though most evidence comes from retrospective, single-center studies.[19][20][24][28][29].

Regulatory Landscape: 42 FDA-approved thoracic radiology AI devices exist, but 98% of pulmonary devices used the 510(k) pathway, indicating approval based on equivalence rather than direct clinical outcome evidence.[10][11][12].

Ventilator AI Impact: Closed-loop ventilation systems reduce VILI, improve patient-ventilator synchrony (>90% detection sensitivity), and shorten ICU stays by 1.5–2.5 days on average, with weaning prediction models achieving AUC 0.87–0.92.[19][20][21][23][24][27].

Algorithmic Bias: AI systematically underdiagnoses disease in female, Black, Hispanic, and low socioeconomic status patients, requiring proactive equity audits and inclusive sampling.[41][42][43][44][46].

Patient Safety: Automation bias and over-reliance on AI predictions pose risks; human oversight and adaptive engagement strategies are essential.[30][49][6].

Implementation Barriers: Successful AI adoption requires multi-year organizational transformation, clinician training, interoperable data infrastructure, and workflow redesign—not just technology deployment.[9][50]

Future Potential: AI integration with genomics, federated learning, neural control interfaces, and large language models promises personalized therapy and global equity, but requires rigorous validation and ethical frameworks.[4][5][14][35].

References

1. The Rise of Artificial Intelligence in Respiratory Primary Care and Pulmonology: A Scoping Review. Soriano JB, Lumbreras S. NPJ Primary Care Respiratory Medicine. 2026;:10.1038/s41533-026-00487-5. doi:10.1038/s41533-026-00487-5.

2. Assessing the Impact of New Technologies on Managing Chronic Respiratory Diseases. Graña-Castro O, Izquierdo E, Piñas-Mesa A, Menasalvas E, Chivato-Pérez T. Journal of Clinical Medicine. 2024;13(22):6913. doi:10.3390/jcm13226913.
3. Advances in Artificial Intelligence Applications for the Management of Chronic Obstructive Pulmonary Disease. Wang M, Li L, Feng M, Liu Z. Frontiers in Medicine. 2025;12:1685254. doi:10.3389/fmed.2025.1685254.
4. Applications of Artificial Intelligence and Machine Learning in Respiratory Medicine. Gonem S, Janssens W, Das N, Topalovic M. Thorax. 2020;75(8):695-701. doi:10.1136/thoraxjnl-2020-214556.
5. Artificial Intelligence/Machine Learning in Respiratory Medicine and Potential Role in Asthma and COPD Diagnosis. Kaplan A, Cao H, FitzGerald JM, et al. The Journal of Allergy and Clinical Immunology. In Practice. 2021;9(6):2255-2261. doi:10.1016/j.jaip.2021.02.014.
6. Artificial Intelligence in U.S. Health Care Delivery. Sahni NR, Carrus B. The New England Journal of Medicine. 2023;389(4):348-358. doi:10.1056/NEJMra2204673.
7. An AI-driven Clinical Care Pathway to Reduce 30-Day Readmission for Chronic Obstructive Pulmonary Disease (COPD) Patients. Wang L, Li G, Ezeana CF, et al. Scientific Reports. 2022;12(1):20633. doi:10.1038/s41598-022-22434-3.
8. The Intervention of Artificial Intelligence to Improve the Weaning Outcomes of Patients With Mechanical Ventilation: Practical Applications in the Medical Intensive Care Unit and the COVID-19 Intensive Care Unit: A Retrospective Study. Lin YH, Chang TC, Liu CF, et al. Medicine. 2024;103(12):e37500. doi:10.1097/MD.0000000000037500.
9. The Effect of Artificial Intelligence-Assisted Pulmonary Rehabilitation on Exercise Capacity: A Systematic Review and Meta-Analysis. Cinkavuk E, Calik E, Vardar-Yagli N. International Journal of Medical Informatics. 2026;211:106336. doi:10.1016/j.ijmedinf.2026.106336.
10. Artificial Intelligence in Acute Respiratory Distress Syndrome: A Systematic Review. Rashid M, Ramakrishnan M, Chandran VP, et al. Artificial Intelligence in Medicine. 2022;131:102361. doi:10.1016/j.artmed.2022.102361.
11. Artificial Intelligence in the Management of Patients With Respiratory Failure Requiring Mechanical Ventilation: A Scoping Review. Viderman D, Ayazbay A, Kalzhan B, et al. Journal of Clinical Medicine. 2024;13(24):7535. doi:10.3390/jcm13247535.
12. Artificial Intelligence and Machine Learning in Acute Respiratory Distress Syndrome Management: Recent Advances. Li S, Yue R, Lu S, et al. Frontiers in Medicine. 2025;12:1597556. doi:10.3389/fmed.2025.1597556.
13. Artificial Intelligence for the Optimal Management of Community-Acquired Pneumonia. Barbieri MA, Battini V, Sessa M. Current Opinion in Pulmonary Medicine. 2024;30(3):252-257. doi:10.1097/MCP.0000000000001055.
14. Can Artificial Intelligence Improve the Management of Pneumonia. Chumbita M, Cillóniz C, Puerta-Alcalde P, et al. Journal of Clinical Medicine. 2020;9(1):E248. doi:10.3390/jcm9010248.
15. An Official American Thoracic Society Research Statement: Comparative Effectiveness Research in Pulmonary, Critical Care, and Sleep Medicine. Carson SS, Goss CH, Patel SR, et al. American Journal of Respiratory and Critical Care Medicine. 2013;188(10):1253-61. doi:10.1164/rccm.201310-1790ST.
16. Randomized Controlled Trials of Artificial Intelligence in Clinical Practice: Systematic Review. Lam TYT, Cheung MFK, Munro YL, et al. Journal of Medical Internet Research. 2022;24(8):e37188. doi:10.2196/37188.
17. Artificial Intelligence-Assisted Clinical Decision Support for Childhood Asthma Management: A Randomized Clinical Trial. Seol HY, Shrestha P, Muth JF, et al. PloS One. 2021;16(8):e0255261. doi:10.1371/journal.pone.0255261.
18. Cost-Effectiveness of Digital Health Interventions for Asthma or COPD: Systematic Review. Ferreira MAM, Dos Santos AF, Sousa-Pinto B, Taborda-Barata L. Clinical and Experimental Allergy : Journal of the British Society for Allergy and Clinical Immunology. 2024;54(9):651-668. doi:10.1111/cea.14547.
19. Technological Maturity and Cost-Effectiveness of Medical AI: A Systematic Review of Health Economic Evaluations. Godoy Junior CA, Boverhof BV, Rutten-van Mölken MPMH, et al. Value in Health : The Journal of the International Society for Pharmacoeconomics and Outcomes Research. 2026;:S1098-3015(26)00041-0. doi:10.1016/j.jval.2026.01.014.

 doi:10.20944/preprints202603.0857.v1

20. Measuring the Impact of AI in the Diagnosis of Hospitalized Patients: A Randomized Clinical Vignette Survey Study. Jabbour S, Fouhey D, Shepard S, et al. JAMA. 2023;330(23):2275-2284. doi:10.1001/jama.2023.22295.
21. The Current Status and Future of FDA-approved Artificial Intelligence Tools in Chest Radiology in the United States. Milam ME, Koo CW. Clinical Radiology. 2023;78(2):115-122. doi:10.1016/j.crad.2022.08.135.
22. Approval of Artificial Intelligence and Machine Learning-Based Medical Devices in the USA and Europe (2015-20): A Comparative Analysis. Muehlematter UJ, Daniore P, Vokinger KN. The Lancet. Digital Health. 2021;3(3):e195-e203. doi:10.1016/S2589-7500(20)30292-2.
23. Clinical Evidence to Support U.S. Food and Drug Administration Review of New Medical Technology in Pulmonary, Sleep and Critical Care Medicine Between 2014 and 2024: A Scoping Review to Support Adoption in Practice. Gardner J, Busam JA, Shah ED. Chest. 2025;:S0012-3692(25)05946-X. doi:10.1016/j.chest.2025.12.012.
24. FDA Perspective on the Regulation of Artificial Intelligence in Health Care and Biomedicine. Warraich HJ, Tazbaz T, Califf RM. JAMA. 2025;333(3):241-247. doi:10.1001/jama.2024.21451.
25. Spirometry Services in England Post-Pandemic and the Potential Role of AI Support Software: A Qualitative Study of Challenges and Opportunities. Doe G, Taylor SJ, Topalovic M, et al. The British Journal of General Practice : The Journal of the Royal College of General Practitioners. 2023;73(737):e915-e923. doi:10.3399/BJGP.2022.0608.
26. Pocket Guide to COPD Diagnosis, Management, and Prevention: 2026 Report. Global Initiative for Chronic Obstructive Lung Disease.
27. Underdiagnosis Bias of Artificial Intelligence Algorithms Applied to Chest Radiographs in Under-Served Patient Populations. Seyyed-Kalantari L, Zhang H, McDermott MBA, Chen IY, Ghassemi M. Nature Medicine. 2021;27(12):2176-2182. doi:10.1038/s41591-021-01595-0.
28. Considering Biased Data as Informative Artifacts in AI-Assisted Health Care. Ferryman K, Mackintosh M, Ghassemi M. The New England Journal of Medicine. 2023;389(9):833-838. doi:10.1056/NEJMra2214964.
29. Algorithmic Encoding of Protected Characteristics in Chest X-Ray Disease Detection Models. Glocker B, Jones C, Bernhardt M, Winzeck S. EBioMedicine. 2023;89:104467. doi:10.1016/j.ebiom.2023.104467.
30. Assessing Socioeconomic Bias in Machine Learning Algorithms in Health Care: A Case Study of the HOUSES Index. Juhn YJ, Ryu E, Wi CI, et al. Journal of the American Medical Informatics Association : JAMIA. 2022;29(7):1142-1151. doi:10.1093/jamia/ocac052.
31. Origins of Racial and Ethnic Bias in Pulmonary Technologies. Sjoding MW, Ansari S, Valley TS. Annual Review of Medicine. 2023;74:401-412. doi:10.1146/annurev-med-043021-024004.
32. Sociodemographic Bias in Clinical Machine Learning Models: A Scoping Review of Algorithmic Bias Instances and Mechanisms. Colacci M, Huang YQ, Postill G, et al. Journal of Clinical Epidemiology. 2025;178:111606. doi:10.1016/j.jclinepi.2024.111606.
33. Bias and Oversight in Clinical AI: A Review of Decision Support Tools and Equity Frameworks. Adegunle F, Chhatwal K, Arab S, et al. Journal of General Internal Medicine. 2026;:10.1007/s11606-026-10229-5. doi:10.1007/s11606-026-10229-5.
34. Artificial Intelligence and Computer-Aided Diagnosis in Diagnostic Decisions: 5 Questions for Medical Informatics and Human-Computer Interface Research. Brunyé TT, Mitroff SR, Elmore JG. Journal of the American Medical Informatics Association : JAMIA. 2025;:ocaf123. doi:10.1093/jamia/ocaf123.
35. Challenges of Artificial Intelligence in Medicine. Aldosari B, Aldosari H, Alanazi A. Studies in Health Technology and Informatics. 2025;323:16-20. doi:10.3233/SHTI250039.
36. Awareness of Racial and Ethnic Bias and Potential Solutions to Address Bias With Use of Health Care Algorithms. Jain A, Brooks JR, Alford CC, et al. JAMA Health Forum. 2023;4(6):e231197. doi:10.1001/jamahealthforum.2023.1197.
37. Health Care Professionals' Concerns About Medical AI and Psychological Barriers and Strategies for Successful Implementation: Scoping Review. Arvai N, Katonai G, Mesko B. Journal of Medical Internet Research. 2025;27:e66986. doi:10.2196/66986.

38. An Integrative Review on the Acceptance of Artificial Intelligence Among Healthcare Professionals in Hospitals. Lambert SI, Madi M, Sopka S, et al. NPJ Digital Medicine. 2023;6(1):111. doi:10.1038/s41746-023-00852-5.
39. Artificial Intelligence in Healthcare: A Scoping Review of Medical Professionals' Acceptance and Institutional Challenges in Implementation. Nesa L, Rony MKK, Chowdhury S, et al. Journal of Evaluation in Clinical Practice. 2025;31(4):e70170. doi:10.1111/jep.70170.
40. Barriers to and Facilitators of Clinician Acceptance and Use of Artificial Intelligence in Healthcare Settings: A Scoping Review. Scipion CEA, Manchester MA, Federman A, Wang Y, Arias JJ. BMJ Open. 2025;15(4):e092624. doi:10.1136/bmjopen-2024-092624.
41. Artificial Intelligence Implementation in Healthcare: A Theory-Based Scoping Review of Barriers and Facilitators. Chomutare T, Tejedor M, Svenning TO, et al. International Journal of Environmental Research and Public Health. 2022;19(23):16359. doi:10.3390/ijerph192316359.
42. Technical/Algorithm, Stakeholder, and Society (TASS) Barriers to the Application of Artificial Intelligence in Medicine: A Systematic Review. Li LT, Haley LC, Boyd AK, Bernstam EV. Journal of Biomedical Informatics. 2023;147:104531. doi:10.1016/j.jbi.2023.104531.
43. Use of Artificial Intelligence in Critical Care: Opportunities and Obstacles. Pinsky MR, Bedoya A, Bihorac A, et al. Critical Care (London, England). 2024;28(1):113. doi:10.1186/s13054-024-04860-z.
44. A Comprehensive Overview of Barriers and Strategies for AI Implementation in Healthcare: Mixed-Method Design. Nair M, Svedberg P, Larsson I, Nygren JM. PloS One. 2024;19(8):e0305949. doi:10.1371/journal.pone.0305949.
45. A Cross Sectional Feasibility Study to Evaluate the Usability and Efficacy of Swaasa AI Platform for Rapid Respiratory Health Assessment. Lotheti SK, Vissamsetti H, Pamarthi K, et al. Scientific Reports. 2025;15(1):38379. doi:10.1038/s41598-025-22215-8.
46. Economic Evaluations of Artificial Intelligence-Based Healthcare Interventions: A Systematic Literature Review of Best Practices in Their Conduct and Reporting. Vithlani J, Hawksworth C, Elvidge J, Ayiku L, Dawoud D. Frontiers in Pharmacology. 2023;14:1220950. doi:10.3389/fphar.2023.1220950.
47. Artificial Intelligence in Chronic Obstructive Pulmonary Disease: Recent Advances in Imaging and Physiological Monitoring. Zhou CY, Restko M, Freije B, Burkes RM. Current Opinion in Pulmonary Medicine. 2025;:00063198-990000000-00290. doi:10.1097/MCP.0000000000001228.
48. Artificial Intelligence for Mechanical Ventilation: Systematic Review of Design, Reporting Standards, and Bias. Gallifant J, Zhang J, Del Pilar Arias Lopez M, et al. British Journal of Anaesthesia. 2022;128(2):343-351. doi:10.1016/j.bja.2021.09.025.
49. Artificial Intelligence in Idiopathic Pulmonary Fibrosis: Advances, Challenges, and Future Directions. Selman M, Buendia-Roldan I, Pardo A. The European Respiratory Journal. 2025;:2501112. doi:10.1183/13993003.01112-2025.
50. Educational Strategies for Clinical Supervision of Artificial Intelligence Use. Abdulnour RE, Gin B, Boscardin CK. The New England Journal of Medicine. 2025;393(8):786-797. doi:10.1056/NEJMra2503232.