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REVIEW

Innovative Applications and Challenges of Artificial Intelligence in the Whole-Course Management of Chronic Obstructive Pulmonary Disease

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Objective: To systematically map how artificial intelligence (AI) can transform whole-course chronic obstructive pulmonary disease (COPD) management across prevention, diagnosis, treatment and rehabilitation within a 4P (Predictive, Preventive, Personalized, Participatory) medicine framework, and to identify actionable strategies for overcoming current barriers.
Methods: A systematic search of PubMed, Web of Science and Embase was performed for articles published between January 2021 and June 2025. This review was conducted following the PRISMA guidelines. Forty empirical studies and reviews that applied AI/ML to COPD prevention, early detection, personalised therapy, exacerbation prediction or pulmonary rehabilitation were critically appraised. Data were extracted on technical foundations, data modalities, algorithms, validation metrics and implementation outcomes.
Results: AI models integrating multimodal data (imaging, wearables, environmental exposures, genomics) achieved AUC ≥ 0.80 for predicting acute exacerbations up to seven days in advance, were associated with a reduction in emergency visits of up to 98% and a lowering of readmission rates by 25–48%. Screening tools using chest X-ray, CT or smartphone sensors attained ≥90% accuracy for early COPD detection in primary-care settings. Personalised treatment optimisation was linked to a 53% lowering of exacerbation risk in best-responding subgroups. Home-based AI rehabilitation platforms increased adherence by >30% without additional equipment. Key implementation challenges include data heterogeneity, limited explainability, digital divide among older adults and unclear regulatory frameworks.
Conclusion: AI is poised to operationalise 4P COPD care, delivering substantial clinical and economic benefits. Future success depends on cross-centre data standards, explainable-AI toolchains, federated learning and inclusive reimbursement policies.
Keywords: chronic obstructive pulmonary disease, artificial intelligence, machine learning, exacerbation prediction, precision medicine, pulmonary rehabilitation

Introduction

Disease Burden and Management Challenges of COPD

Chronic obstructive pulmonary disease (COPD) is a chronic inflammatory lung disorder characterized by persistent airflow limitation. Its high global prevalence, disability, and mortality render COPD a major public health challenge.[1] It currently ranks as the fourth leading cause of death worldwide, surpassed only by ischaemic heart disease, stroke, and cancer. The most recent Global Burden of Disease Study 2021 estimates that COPD caused 3.72 million deaths and 798 million disability-adjusted life-years (DALYs) in a single year, while global incident cases reached 16.9 million.[2,3]

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These figures underscore an ongoing upward trajectory that is projected to continue beyond 2030.[4] The disease predominantly affects middle-aged and older adults and is strongly associated with long-term tobacco smoking, ambient and household air pollution, and occupational exposures. Patients typically present with chronic cough, sputum production, and progressive dyspnoea, symptoms that markedly impair quality of life and predispose to acute exacerbations, cor pulmonale, and respiratory failure.[5]

Despite continual refinements in COPD management strategies, several persistent challenges hinder optimal clinical care. First, early diagnosis remains elusive, largely because of the limited availability and underutilisation of spirometry.[6] Second, acute exacerbations are difficult to predict accurately, precipitating recurrent hospitalisations, heightened mortality risk, and escalating healthcare costs.[7] Third, therapeutic regimens are insufficiently individualised, resulting in marked inter-patient variability in treatment response and suboptimal outcomes for many. Fourth, long-term adherence to pharmacological and non-pharmacological therapies is poor, undermined by adverse effects, financial constraints, and limited patient knowledge.[8] Finally, pulmonary rehabilitation resources are unevenly distributed, many regions lack specialised facilities and trained personnel, restricting patients' access to effective rehabilitative interventions.[9] Collectively, these barriers—delayed diagnosis, imprecise exacerbation prediction, absence of precision medicine approaches, poor adherence, and inequitable access to rehabilitation—underscore the urgent need for more efficient, accurate, accessible, and patient-centred management tools to improve both prognosis and quality of life for individuals living with COPD.

Opportunities in the Intelligent Era: Convergence of Artificial Intelligence and Digital Health

The rapid advancement of technology has ushered in an "intelligent era" characterized by the integration of the Internet of Things (IoT), wearable devices, cloud computing, and big data,[10] bringing profound transformations to the healthcare sector. In the management of chronic obstructive pulmonary disease (COPD), digital health technologies (DHTs) demonstrate significant potential:[11] remote monitoring systems enable real-time collection of physiological data to facilitate early intervention; mobile applications provide personalized education to enhance self-management skills and treatment adherence; and the aggregation of multi-source data lays the foundation for precision medicine.[12] However, these technologies also introduce challenges such as massive data volume and high heterogeneity,[13] which are difficult to handle effectively using conventional methods. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has emerged as a key solution,[14] capable of integrating multimodal data, uncovering latent patterns, quantifying disease risks, and supporting clinical decision-making—for instance, predicting COPD exacerbations and generating personalized management recommendations.[15]

The impact of AI in COPD care extends beyond data processing and risk prediction. As shown in Figure 1, it is catalyzing a paradigm shift toward the 4P medicine framework—predictive, preventive, personalized, and participatory Predictively, AI synthesizes multidimensional patient profiles to anticipate disease progression and imminent exacerbations,[16] Preventively, AI-driven analytics generate individualized risk-mitigation strategies. Personalization is achieved through AI-guided tailoring of therapeutic regimens to each patient's unique phenotypic and genotypic signature. Finally, participatory engagement is facilitated by mobile platforms that empower patients to co-manage their disease, thereby improving adherence and quality of life.[17] In sum, the synergy between AI and DHTs redefines COPD management across the entire care continuum, offering a viable path to operationalize 4P medicine and ultimately improving both prognosis and patient-centered outcomes.

Research Gaps and Objectives of This Review

Despite growing research on AI in COPD management, existing reviews remain fragmented, often focusing on narrow applications—such as imaging or exacerbation prediction—without providing a holistic view of whole-course care or adequately examining the technical foundations, data workflows, and real-world implementation barriers. This fragmentation limits their practical value for clinicians, researchers, and policymakers seeking to implement AI solutions.

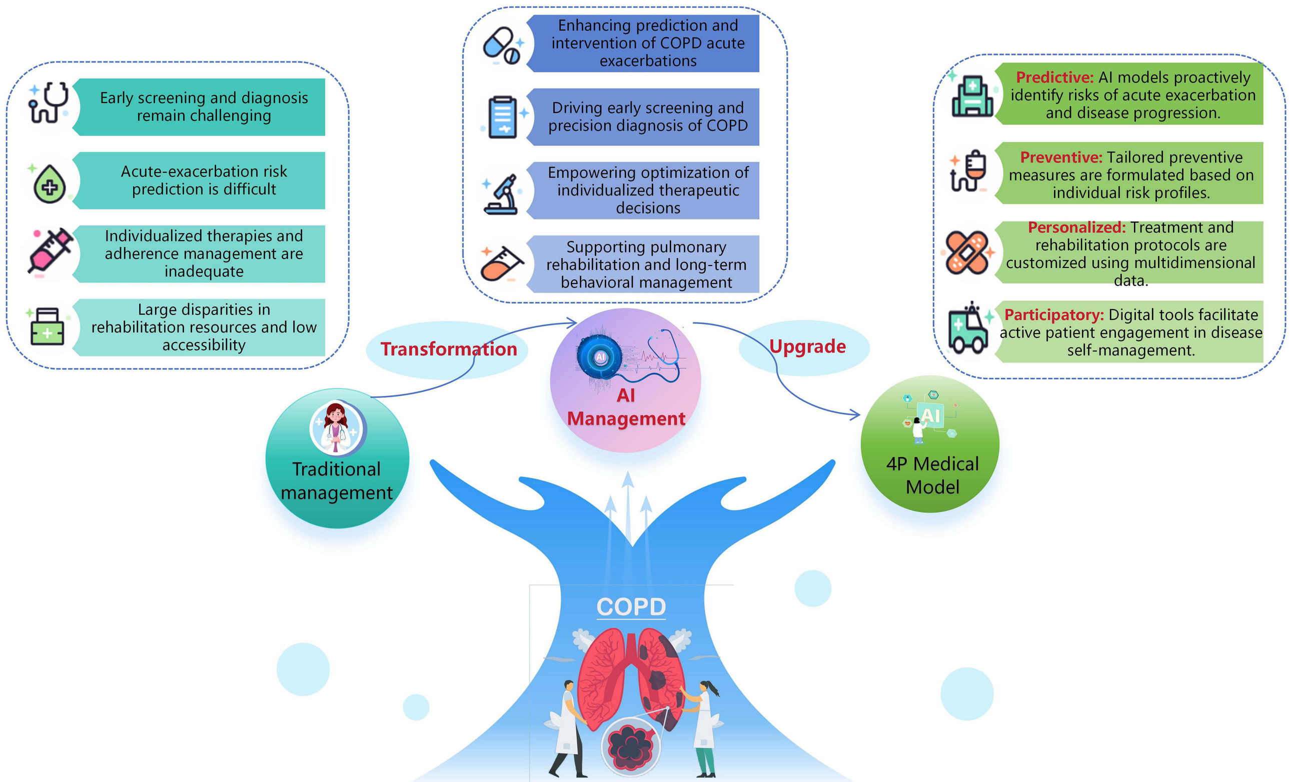

Figure 1 AI-Driven 4P Framework for Transforming COPD Management from Traditional Care to Precision Medicine. This figure illustrates the paradigm shift from reactive care to a proactive, AI-powered model. It maps specific AI solutions to key challenges in chronic obstructive pulmonary disease (COPD) management, operationalizing the 4P (Predictive, Preventive, Personalized, Participatory) medicine framework.

Furthermore, critical dimensions such as algorithmic fairness, data sovereignty, and the evolving regulatory landscape for AI in healthcare are often overlooked, yet are pivotal for building trust and ensuring equitable implementation.

To address these gaps, this review systematically analyzes AI applications across all stages of COPD whole-course care—prevention, diagnosis, treatment, and rehabilitation—by examining technical foundations, data processes, and practical implementation. Specifically, our objectives are to: (1) map the current landscape of AI technologies and multimodal data sources used throughout the COPD care continuum; (2) synthesize empirical evidence on the efficacy and performance of these AI applications; (3) critically examine the technical, ethical, and societal challenges impeding real-world deployment; and (4) propose a structured framework and actionable future directions for developing and implementing trustworthy AI systems in COPD management. Through this integrated approach, the study seeks to establish a structured framework for AI-enabled COPD management and offer evidence-based guidance for both research and practice. (The key findings of this review are shown in Figure 2).

This review distinguishes itself by integrating the evidence into a cohesive 4P medicine framework and providing a critical analysis of implementation pathways, thereby offering a novel and structured roadmap that is not available in the existing, more narrowly focused literature.

Overview of the Article Structure

This review is structured as follows: Chapter 2 describes the research methodology, including literature search strategy, inclusion and exclusion criteria, data extraction, and quality assessment. Chapter 3 comprehensively examines AI applications across the core stages of COPD management—prevention, diagnosis, treatment, and rehabilitation—and delves into the supporting technical principles and data-flow mechanisms through multidimensional analysis. Chapter 4 systematically addresses challenges in AI implementation, including technical, social, and ethical issues, and proposes corresponding mitigation strategies. Chapter 5 provides a comprehensive discussion of AI applications in COPD care,

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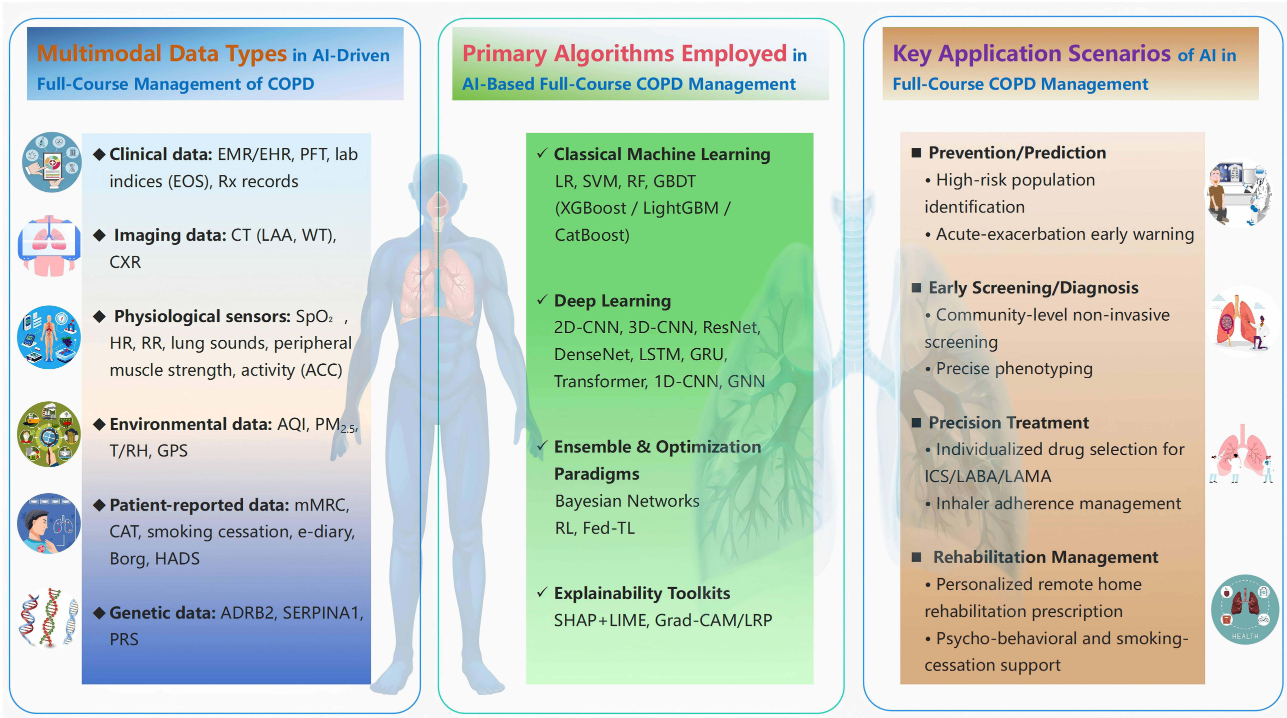

Figure 2 Key Findings of this Review: AI-Enabled End-to-End Chronic Obstructive Pulmonary Disease Management. This figure outlines the core ecosystem for AI in COPD care, integrating multimodal data (eg, EHR, PFT, CT, CXR, SpO_2), a hierarchy of AI algorithms (from LR/SVM/RF to CNN/LSTM/Transformer and XAI tools like SHAP/LIME), and their translation into clinical applications across prevention, diagnosis, treatment, and rehabilitation.

summarizing advantages, limitations, and offering policy and practice recommendations. Finally, Chapter 6 concludes by summarizing key findings and suggesting directions for future research and implementation.

Methods

Literature Search Strategy

A systematic search was conducted across three electronic databases—PubMed, Web of Science Core Collection, and Embase—to identify relevant articles published between January 2021 and June 2025. The search strategy was designed around core concepts: "chronic obstructive pulmonary disease" (COPD), "artificial intelligence" (AI)/ "machine learning" (ML), and key management areas (eg, prevention, diagnosis, treatment, rehabilitation). A Boolean approach combining controlled vocabulary (eg, MeSH, Emtree) and free-text keywords was employed. Manual screening of reference lists supplemented the electronic search to ensure comprehensive and current coverage. This timeframe was selected to include the most recent advances in AI applications for whole-course COPD management.

Study Selection and Eligibility Criteria

All identified records were imported into EndNote for duplicate removal, and the subsequent study selection followed the PRISMA 2020 guidelines, as detailed in the flow diagram (Figure 3).

Studies were included if they: (1) applied AI/ML methodologies to any stage of COPD management; (2) were original research or substantive reviews; and (3) were published in English within the specified timeframe. Studies were excluded if they were: (1) conference abstracts, editorials, or letters without detailed methods; (2) not focused on COPD; (3) lacking a core AI/ML component; or (4) unavailable in full text.

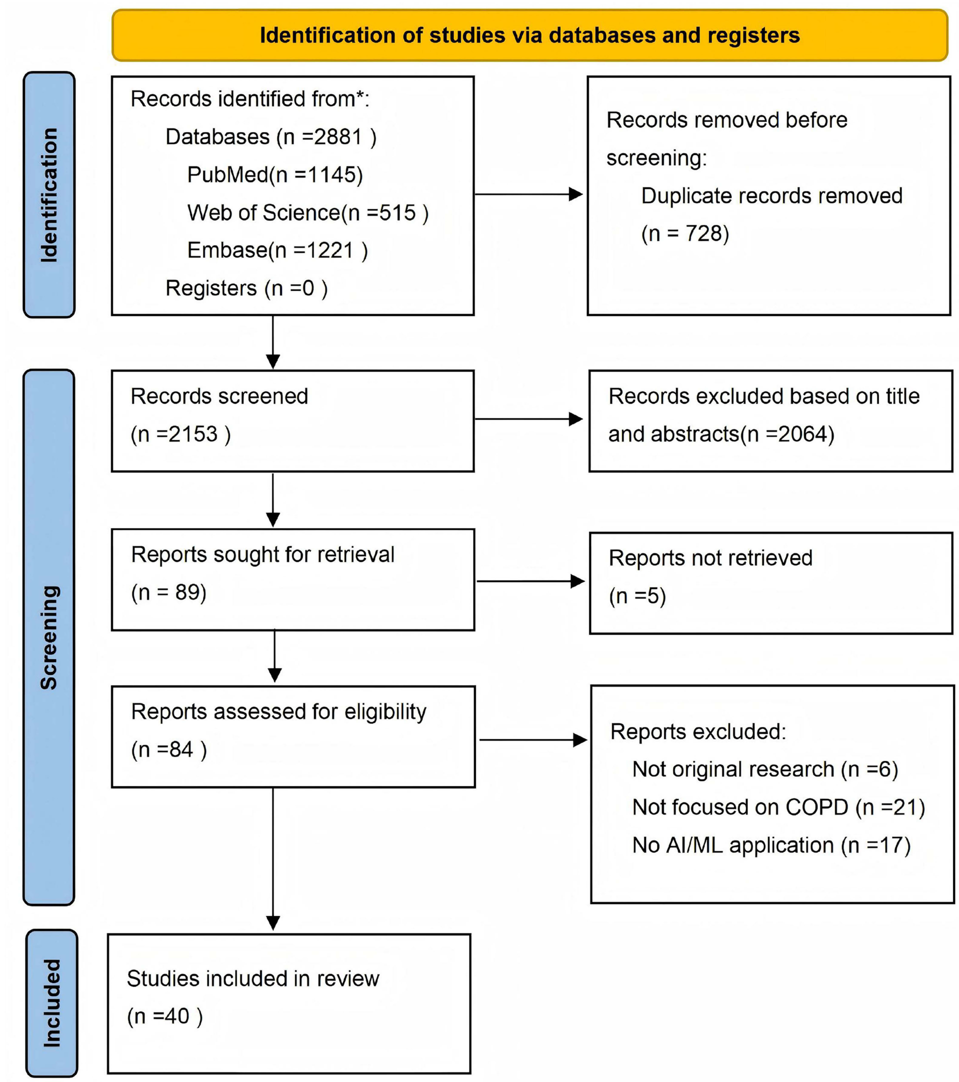

Figure 3 PRISMA Flowchart of Studies Through the Selection Process.

Data Extraction and Quality Assessment

Key data from included studies were extracted, including study design, data sources, AI algorithms, key outcomes, and performance metrics.

A formal quality and risk of bias appraisal was performed to assess the robustness of the evidence. Studies were evaluated across domains such as study design, sample size, data quality, and validation methods. Each study was assigned an overall quality rating (High, Moderate, or Low), which is summarized in the "Risk of Bias / Study Quality" column of Tables 1–4.

Data Synthesis

Given the heterogeneity in AI applications and outcomes, a narrative synthesis was conducted. Findings were structured thematically according to the COPD care continuum to provide an integrated overview of AI technologies, their clinical applications, and implementation challenges.

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Table 1 Snapshot of Key Empirical Studies on Clinical Applications of AI-Driven Prediction and Intervention for COPD Exacerbations

First Author and Year	Research Design and Sample Size	Core Data/Mode	Main Algorithm	Predicted Outcome and Follow-Up	Performance Indicators	Clinical Significance	External Validation	Risk of Bias/Study Quality
Jeon ET 2025[18]	Retrospective cohort study; n=10,492	PFT graph + clinical variables	CNN + feature fusion	Moderate-severe and severe AECOPD; Ten years	AUC 0.755/0.713 vs traditional $P < 0.05$	Suitable for patients with stable long-term prognosis and no history of aggravation	No	Moderate
San Jose Estepar R 2025[19]	Imaging cohort; n=4369	Chest CT → AIMP mucus plug score	3D CNN lung lobe segmentation	Death & severe AECOPD	Cindex 0.717 vs visual 0.715 ($p = 0.02$)	AI quantification of mucus plugs is more sensitive and has higher prognostic value	No	Moderate
Kor CT 2022[20]	Retrospective case-control study; n=606	EHR + Laboratory	GBM(RFE)	First AECOPD	AUC 0.833 (95% CI 0.745–0.921)	SHAP visualization aids in clinical interpretation	No	Moderate to High
Glyde H 2024[21]	Prospective digital cohort; n=506	myCOPD self-report + sensor	AdaBoost/ EasyEnsemble	In the next 1–8 days, AECOPD; APP follow-up	Sens 67%/35%; Spec 65%/ 89%	A high NPV can safely rule out the risk of worsening within 8 days.	No	Moderate
Yin H 2024[22]	Single-center prospective cohort; n=66	Portable pulmonary function meter + electronic stethoscope	CatBoost	The next 5 days: AECOPD	AUC 0.972 (95% CI 0.962–0.981)	Remote monitoring is superior to traditional time series	No	High
Chaudhary M 2023[23]	Multicenter longitudinal cohort; Development: n = 1956/External validation: n = 6965	Quantitative chest CT + clinical variables	Multivariate logistic regression classifier	≥ 1 time/year AECOPD (3 years); SPIROMICS 3 years, COPDGene independent period	Developed AUC of 0.854; for the past 3 years, AUC was 0.931; external validation AUC was 0.768	Quantitative CT imaging outperforms traditional medical history/BODE; the potential of CT biomarkers is significant	Yes	Low to Moderate
Patel N 2021[24]	Prospective observational cohort; n=90	COPD Predict™ App conducts daily self-assessment of well-being + portable pulmonary function FEV1 + fingertip blood CRP	Decision tree (threshold model)	7 days in advance for AECOPD (median)	Sens 97.9%; Spec 84%; PPV 38.4%; NPV 99.8%	Emergency visits ↓ 98%, personalized alerts	No	High
Safari A 2022[25]	Retrospective secondary analysis + external validation; Development: n = 1803/Validation: n = 1091	EHR/clinical variables	ACCEPT 2.0 re-calibration	≥ 2 moderate or ≥ 1 severe AECOPD within 12 months; 3 years	AUC 0.76 vs history of exacerbation 0.68; reduction in simplified version AUC < 0.011	Net reclassification index ↑, stable across cohorts	Yes	Moderate
Snyder L 2025[26]	12-week open-label study; n=336	ProAir Digihaler sensor data Gradient-boosting trees	Gradient-boosting trees	The next 5 days: AECOPD; 12 weeks	AUC 0.77 (95% CI 0.71–0.83)	Digital inhaler real-time monitoring	No	Moderate
Turcatel G 2025[27]	Retrospective EHR cohort; n=1331 934	Structured data of EHR	XGBoost, SHAP	AECOPD within the next 6 months	AUC 0.964	Discover potential protective factors such as vitamins and statins	No	Low

Notes: The performance metrics (eg, AUC, Sensitivity, Specificity) are as reported in the original studies. Follow-up durations vary across studies. External Validation: Yes indicates that the model was evaluated on a completely independent cohort, separate from the development dataset. No indicates validation was performed only internally (eg, cross-validation on the same dataset). Risk of Bias / Study Quality: This is a synthesized assessment based on key methodological aspects: Low: Typically associated with large sample sizes, prospective or multicenter designs, and/or robust external validation. Moderate: Typically associated with moderate sample sizes, retrospective designs in large datasets, or single-center prospective studies without external validation. High: Typically associated with small sample sizes, single-center retrospective designs, or studies without clear validation procedures.

Abbreviations: COPD, chronic obstructive pulmonary disease; AECOPD, Acute Exacerbation of COPD; AUC, Area Under the Curve; Sens, Sensitivity; Spec, Specificity; PPV, Positive Predictive Value; NPV, Negative Predictive Value; EHR, Electronic Health Record; CT, Computed Tomography; CNN, Convolutional Neural Network; GBM, Gradient Boosting Machine.

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Table 2 Snapshot of Clinical Empirical Evidence on AI-Driven Early Screening and Precision Diagnosis of COPD

First Author and Year	Research Design and Sample Size	Core Data/Mode	Main Algorithm	Predicted Outcome and Follow-Up	Performance Indicators	Clinical Significance	External Validation	Risk of Bias/Study Quality
Saad M M 2023[28]	Cross-sectional descriptive study; n=80	Non-enhanced chest CT + Pulmonary function (FEV1/FVC)	CNN Automatic Segmentation	Real-time COPD grading (GOLD 1–4)	Distinguishing between severe and moderate cases: AUC 0.86 (LAA - 950%)	AI-CT can quantify the severity of COPD	No	High
Liang H 2025[29]	Multicenter cross-sectional study; training group n = 31,267, external validation group n = 1142 cases, physician control group n = 110	Chinese EHR text	NLP Feature Extraction + LightGBM Classification	Real-time Top 1/Top 3 diagnosis	Top1 F1: 0.71 (intra)/0.65 (extra), > Physician & ChatGPT4	AI-NLP can provide real-time and accurate assistance in the initial diagnosis of respiratory diseases	Yes	Low to Moderate
Wang X 2023[30]	Cross-sectional study; n=5807	34 questionnaires + physical examination variables	Weighted Logistic	COPD risk binary classification	F1: 0.290, G-mean: 0.660	Automated COPD high-risk identification driven by questionnaires	No	High
Taloba A 2025[31]	Cross-sectional study; n=920	MFCC lung sound recordings	FFS feature selection + SVM-KNN fusion classification	COPD vs Healthy binary classification	Accuracy: 94%	Early identification of COPD is superior to traditional auscultation and can be integrated into portable devices	No	Moderate
Zou X 2024[32]	Multicenter retrospective study; n=1055	Positive chest X-ray (CXR) + clinical parameters	Deep transfer learning + integrated model integrating imaging and clinical features	COPD identification + COPD grading (3/5 grades)	AUC: Intra-test 0.969/ Extern-test 0.934; Three/ five-classification 0.894/ 0.852	Low-radiation and efficient grading, superior to single modality	Yes	Moderate
Idrisoglu A 2024[33]	Cross-sectional study; n=1246	Baseline acoustic + MFCC features	CatBoost	COPD vs Healthy binary classification	AUC: 82%, AP: 76%, Accuracy: 97%	Non-invasive voice screening, applicable via phone/remote connection	No	Moderate
Choi EA 2021[34]	Cross-sectional study; n=36	Genes + clinical indicators	RF	COPD mild/severe grading	AUC: 0.886	The first COPD severity prediction model based on genes and clinical characteristics.	No	High
Vishalatchi K 2025[35]	Retrospective cohort; n=1142	EHR clinical text + personal structured information	LLM-NLP pipeline + multi-agent architecture	COPD acute exacerbation vs Other respiratory diseases	Accuracy: 80%; F1: 0.73	The LungDiag system has been launched, improving diagnostic efficiency.	No	Moderate
Chawla J 2025[36]	Cross-sectional study; n≈64 k	Chest CT scan images	Improved ResNet50V2 + New Feature Pyramid Network (FPN)	CT scan shows presence or absence of COPD; patient level shows COPD diagnosis	Single image classification accuracy: 98.91%; Patient-level recognition accuracy ≈ 95.5%	A fully automatic, rapid, and highly accurate CT-COPD screening tool, reducing missed diagnoses.	No	Low
Zhu Z 2024[37]	Cross-sectional study; n=2983	Chest CT + VAE deep features + PyRadiomics imaging omics + questionnaire variables	Multimodal Fusion DL	COPD diagnosis	AUC: 0.971	The multimodal strategy has been significantly improved, and is easy to deploy.	No	Moderate

Notes: Performance metrics were derived from the respective original studies. The datasets and validation methods (eg, internal/external validation) differ across the listed studies. External Validation: Yes indicates that the model was tested on an external population or dataset from a different center/timeframe. No indicates all evaluations were performed on the initial study population. Risk of Bias / Study Quality: This overall rating considers study design, sample size, and validation: Low: Assigned to large, multicenter studies with external validation. Moderate: Assigned to studies with reasonable sample sizes and solid methodology but lacking external validation, or to externally validated studies with smaller samples. High: Assigned to studies with high risk of overfitting (eg, very small sample sizes) or significant methodological limitations (eg, single-center cross-sectional design without validation).

Abbreviations: COPD, chronic obstructive pulmonary disease; AUC, Area Under the Curve; F1, F1-Score; GOLD, Global Initiative for Chronic Obstructive Lung Disease; EHR, Electronic Health Record; CT, Computed Tomography; CXR, Chest X-Ray; CNN, Convolutional Neural Network; NLP, Natural Language Processing; SVM, Support Vector Machine.

Table 3 Snapshot of Key Empirical Studies on AI-Empowered Optimization of Personalized Treatment Decisions in COPD

First Author and Year	Research Design and Sample Size	Core Data/Mode	Main Algorithm	Predicted Outcome and Follow-Up	Performance Indicators	Clinical Significance	External Validation	Risk of Bias/Study Quality
Verstraete K 2023[38]	Secondary analysis of RCT SUMMIT +IMPACT (n≈14K)	Clinical trial structured data	Causal Forest	Individualized intervention effect (ITE); Follow-up until the end of the trial	Q-score: 0.61/0.21; actual aggravation rate decreased by 0.54 and 0.53 respectively ($p < 0.001$)	Precise ICS/LABA/LAMA selection, integrated into CDSS	No	Low
Arnold K.2022[39]	Post-market collaborative application research; Not disclosed	Mobile camera + real-time AI guidance	Kata® Platform: AI + Computer Animation + Augmented Reality	Correct usage rate of the device	Correct usage rate increased by approximately 75%	75% market inhalers compatible, real-time home training	Unclear	Moderate
Mariani S 2021[40]	Single-center retrospective cohort study; n≈1000	Original EHR without cleaning	AutoML	Recommendations for diagnosis, classification and treatment of COPD; 3 months or 12 months	LAMA recommendation: kNN ROC-AUC 0.87; Diagnosis: Linear SVC ROC-AUC 0.94–0.96	Zero configuration embedded in grassroots HIS, real-time individualized plan	No	Moderate
Pereira J 2023[41]	Single-center prospective observational study; n=91	Life signs + environmental parameters	Ensemble Learning	Early intervention for the deterioration of the condition; Six months	Pilot verification in Portugal, high satisfaction of medical staff (> 4/5)	Low-cost access to home IoT, globally scalable	No	High
Park S 2025[42]	Retrospective single-center study; n=4360	Routine Indicators of Spirometer	MLP	Positive predictive value of MBPT	AUC 0.701; Accuracy 0.758; F1 0.853	Embedding grassroots pulmonary function devices to replace expensive provocation tests	No	Moderate
Nikolaou V 2022[43]	Cross-sectional study; n=13,102	16 Blood Biomarkers + Demographic Information	Recursive feature selection (RFE) + Multiple model ML	Whether respiratory system treatment is received	Accuracy 69%, Sensitivity 64%, Specificity 71%	For the first time, a combination of biomarkers for "treatment diagnosis" in respiratory diseases is proposed, which can guide precise treatment	No	Moderate
Liao KM 2021[44]	Retrospective multicenter study; n=5061	EHR structured data	XGBoost/RF/ LGBM	Acute respiratory failure after hospitalization, ventilator dependence, and death	AUC 0.817 (death), 0.804 (acute respiratory failure), 0.809 (ventilator dependence)	Zero-cost access to HIS, immediate risk stratification	Yes	Moderate
Yakutcan U 2021[45]	Discrete Event Simulation (DES) + Health Economics Mo Simulation; n = 1540	HES inpatient data, outpatient/community activity data, literature parameters	DES simulation + cost-benefit analysis	Changes in death, hospitalization, bed days, and QALY after a 10–30% increase in PR referral rate	BCR = 5.91; death ↓ 3.56, hospitalization ↓ 4.90, bed days ↓ 137.31, QALY ↑ 5.53	The first hospital-level COPD operation-economic comprehensive model, providing evidence-based basis for expanding PR coverage policies	No	Moderate
Domínguez J 2024[46]	Hybrid method validation; 20 simulated cases of COPD + 5 respiratory doctors	GOLD 2017 guidelines in EHR + comorbidity data	TMR ontology + ABA + G explainable argumentation framework	OPD symptom grading and individualized treatment plans	Doctor agreement rate 97% (symptom assessment), 98% (treatment plan)	The first interpretable, non-patent EHR internal guideline conflict handling system	No	Moderate
Ellertsson S 2023[47]	Retrospective diagnostic accuracy study; n=2000	Clinical text records before outpatient visits (CTN)	LASSO-regularized logistic regression model (RSTM)	10-level risk score before visit	NPV reaches 1.00, sensitivity 74%; CXR referral reduced by approximately 1/3, antibiotic prescriptions reduced by 10–15%	Automated triage AI tools at the grassroots level, reducing unnecessary face-to-face consultations, CXR, and antibiotic use	No	Moderate

Notes: ITE, Individual Treatment Effect. Outcomes and performance metrics are specific to the cohorts and methodologies of the cited studies. External Validation: Yes indicates the AI strategy or model was tested in a setting external to its development environment (eg, a different clinic or EHR system). Risk of Bias / Study Quality: Assessment is tailored to interventional/decision-support studies: Low: Includes secondary analyses of RCTs or multicenter studies with external validation. Moderate: Includes well-conducted single-center retrospective or prospective studies. High: Includes small-scale pilot studies, simulations without clinical implementation, or studies with high risk of confounding.
Abbreviations: COPD, chronic obstructive pulmonary disease; RCT, Randomized Controlled Trial; ITE, Individual Treatment Effect; EHR, Electronic Health Record; ICS, Inhaled Corticosteroid; LABA, Long-Acting Beta2-Agonist; LAMA, Long-Acting Muscarinic Antagonist; AUC, Area Under the Curve; ROC, Receiver Operating Characteristic; QALY, Quality-Adjusted Life Year.

Table 4 Snapshot of Key Empirical Studies on AI-Supported Pulmonary Rehabilitation and Long-Term Behavioural Management in COPD

First Author and Year	Research Design And Sample Size	Technical Approach and Mode	Main Algorithm/ Architecture	Key Outcome Indicators	Effectiveness	Clinical Significance	External Validation	Risk of Bias/Study Quality
Chen X 2021[48]	Single-center, randomized controlled trial; n=122	Intelligent resistance inhalation muscle training + intelligent monitoring	Deep learning	Overall therapeutic effect (clinical control + effectiveness) and improvement in blood gas	The overall efficiency was 97.5% vs 80% ($P < 0.05$)	Significantly improves lung function and blood gas in patients with stable COPD, outperforming traditional training methods	No	Moderate
Tang WR 2024[49]	Single-center, cross-over pilot study; n=12	RGBD zero-contact chest and abdomen motion tracking; PowerLab 26T lung volume measurement for real-time lung volume	MediaPipe posture estimation + correlation analysis	Thoracic wall displacement, changes in lung capacity	$r = 0.90$; lung capacity increased by 0.28 L ($P < 0.05$)	Zero-marking, zero-contact system, convenient for postoperative or home-based pulmonary rehabilitation	No	High
Cao L 2023[50]	Single-center retrospective cohort; n=37	Single-eye RGB video + synchronous collection of biochemical and pulmonary function indicators	ResNet18-CNN-LSTM	Binary classification of rehabilitation effect: improvement vs deterioration	Accuracy rate 90.6%, AUC 0.97	Deployed with a regular camera, self-recovery	No	High
Arvind D K 2022[51]	Pre-research on Point-to-Point Care System (POCS); n = 9 rehabilitation therapists	Respeck chest sensor + App + virtual pet	Machine learning classifier	Accuracy rate of action recognition	Accuracy rate: 93%; Compliance improved	Home-based unsupervised standardized rehabilitation and remote follow-up	No	High
Fan C 2022[52]	Single-center experimental study; n=42	Camera + CNNLSTM action recognition	Lightweight Hybrid Model	Accuracy rate of action recognition	Overall accuracy rate: 82.35%	Real-time assessment of rehabilitation standardization, applicable to unsupervised home scenarios	No	High
Bogacz K 2024[53]	Multicenter study; n=80	PulmoRehab AI remote rehabilitation	Personalized AI solution	6MWD, FEV_1, blood oxygen	Significant improvement ($P<0.05$)	Zero equipment requirements, scalable for grassroots levels	Yes	Moderate
Guo L 2021[54]	Single-arm clinical trial; n=18	Camera + human normalization + SVM	DTW + SVM	Accuracy of action assessment and consistency with expert ratings	Accuracy rate: 98.4%; $r = 0.967$	Home-based rehabilitation training and real-time assessment can be directly deployed on home computers	No	High
Jiang Y 2025[55]	Three-arm RCT; n=159	HAPAGaPR gamifies remote rehabilitation	HAPA + gamification	Compliance, quality of life	Compliance: 63.27% vs 30.61% ($p = 0.001$); Significant improvement in CAT: 69.4% vs 26.5%, $p < 0.001$	Low-cost deployment of mobile phones/televisions	No	Moderate
Benzo M 2025[56]	Secondary analysis; n=375	HBPR + health coach	Structural Equation Model	Physical and emotional quality of life	The intervention significantly enhanced the ability ($P < 0.01$) and relevance ($P < 0.01$)	Enhance patients' sense of ability and relevance, promote autonomy, and improve quality of life	No	Moderate
Farrús M 2021[57]	Observational study; n=59	Portable recording device collects voice samples + analyzes voice features	Praat software + Random Forest	Changes in voice characteristics; accuracy of COPD detection; accuracy of FEV1 prediction	COPD detection accuracy: 72%; FEV1 prediction accuracy: 75%.	Monitor the condition of COPD patients through voice analysis	No	High

Notes: 6MWD, 6-Minute Walk Distance; HAPA, Health Action Process Approach. The outcome measures and significance levels (p-values) are as reported in the original investigations. External Validation: For rehabilitation studies, Yes indicates the system or algorithm was tested on a participant cohort distinct from the one used for development/training. Risk of Bias / Study Quality: Given the prevalence of early-stage feasibility studies in this domain, ratings are interpreted accordingly: Low: Multicenter trials or RCTs with adequate sample sizes. Moderate: Single-center RCTs or larger observational studies. High: Small pilot studies (n<20), single-arm trials, or studies without control groups and with limited statistical power.

Abbreviations: COPD, chronic obstructive pulmonary disease; 6MWD, 6-Minute Walk Distance; FEV1, Forced Expiratory Volume in the first second; HAPA, Health Action Process Approach; CAT, COPD Assessment Test; RGBD, Red-Green-Blue-Depth; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; SVM, Support Vector Machine.

AI in Whole-Course COPD Management: Technical Foundations, Data-Flow Governance, and Current Applications

AI Prediction and Intervention for Acute Exacerbation of COPD

Technical Foundations and Data Flows

Acute exacerbations of COPD accelerate lung function decline and increase mortality, making early prediction and intervention essential.[58] AI models integrate multimodal dynamic data to enable risk stratification, early warning, and personalized decision support. Core data sources include: (i) mobile app-recorded symptom diaries; (ii) wearable-monitored physiological parameters (eg, SpO_2, heart rate, respiratory rate);[59] (iii) accelerometer-based activity data;[60] (iv) environmental exposure metrics (eg, air quality via API); and (v) historical clinical records from EHRs (eg, prior exacerbations, medication history).[61]

Advancements in Clinical Evidence

A growing body of evidence supports the effectiveness of artificial intelligence in predicting and preemptively managing acute exacerbations of COPD. By leveraging diverse data sources—including imaging, wearable sensors, and electronic health records—coupled with machine and deep learning approaches, AI enables high predictive accuracy and meaningful clinical integration, significantly reducing hospitalizations through early intervention. Key studies demonstrate robust outcomes: Jeon et al[18] developed the AIPFTClin model, combining pulmonary function images and clinical variables to achieve AUCs of 0.755 and 0.713 for moderate-to-severe and severe exacerbations, sustaining performance over 10 years. Patel et al[24] implemented a decision-tree algorithm in the COPDPredict™ app, enabling 7-day advance predictions with 97.9% sensitivity and 84.0% specificity, and reducing ED visits by 98%. Chaudhary et al[23] used CT biomarkers to develop a model with an AUC of 0.854, outperforming both exacerbation history and the BODE index.

These studies, along with other significant contributions—including advances in mucus-plug detection,[19] interpretable machine learning,[20] mobile health integration,[21] and multimodal data fusion[22,25–27]—are comprehensively summarized in Table 1.

AI-Driven Early Screening and Precision Diagnosis of COPD

Technical Foundations and Data Flows

Artificial intelligence is transforming early screening and diagnostic pathways for COPD by enhancing detection rates in community settings, improving diagnostic accuracy, and enabling precise phenotyping—key enablers of personalized therapy.[62] While traditional screening reliant on pulmonary-function tests (PFTs) faces challenges in primary care, AI-powered tools such as portable devices and mobile applications facilitate an integrated "screening–differentiation–phenotyping" workflow, significantly boosting clinical efficiency.

Multimodal data fusion underpins these advances, incorporating: time-series FEV_1/FVC curves from portable spirometers; quantitative emphysema indices and airway-wall thickness from low-dose CT; cough-sound features captured via smartphones;[63] electronic patient-reported outcomes (eg, mMRC/CAT);[64] and physiological trends (eg, SpO_2, heart rate) from wearables.[65] Integration of these heterogeneous data streams allows AI models to effectively discriminate COPD from asthma, heart failure, and other diseases with symptomatic overlap.

Advancements in Clinical Evidence

The integration of artificial intelligence into COPD screening and diagnosis is advancing through diversified technical approaches and strengthened real-world clinical validation. Innovations leveraging imaging, acoustics, and electronic health records facilitate earlier detection and improved disease stratification beyond conventional pulmonary function tests. Notably, Liang et al[29] developed the LungDiag system using multi-center EHRs, elevating the top-1 diagnostic F1-score from 0.44 by human experts to 0.651 in 1142 real-world cases. Zhu et al[37] proposed a multimodal model combining CT-based deep learning, radiomics, and questionnaires, achieving an AUC of 0.971 in 2983 scans and outperforming single-modality methods. Additionally, Chawla et al[36] introduced an enhanced ResNet50V2-based system trained on ~64,000 CT scans, which attained 98.91% accuracy and correctly identified 234 out of 245 cases, demonstrating high sensitivity even for small lesions.

Additional influential studies—including those utilizing voice biomarkers,[33] chest X-ray imaging,[32] lung sound analysis,[31] and EHR-based natural language processing[35]—are comprehensively summarized in Table 2. Together, these works provide a broad overview of innovative algorithmic strategies, validation outcomes, and clinical relevance, reflecting the diverse and rapidly evolving landscape of AI applications in COPD diagnosis.

Personalized Treatment Decision Optimization Enabled by AI

Technical Foundations and Data Flows

Artificial intelligence is advancing COPD treatment into a precision medicine framework, enabling individualized pharmacological selection, prediction of therapeutic response, improved inhaler adherence, and support for interventional therapies such as bronchoscopic lung volume reduction.[66] By moving beyond traditional trial-and-error approaches, AI integrates multidimensional dynamic data to build evidence-based decision systems that are already demonstrating potential to redefine treatment pathways.

The underlying data architecture incorporates six key information types: clinical phenotypes and biomarkers (eg, blood eosinophil counts); genetic polymorphisms (eg, ADRB2 receptor genotypes);[67] historical medication responses; home-monitored pulmonary function trends (eg, weekly FEV_1 variability);[68] CT-derived quantitative imaging features (airway-wall thickness, emphysema index); and patient-reported outcomes (PROs)[69] Together, these elements form a comprehensive computational foundation for predicting treatment efficacy and guiding personalized care plans.

Advancements in Clinical Evidence

Recent real-world evidence confirms AI's expanding role in guiding individualized COPD management. By integrating heterogeneous data streams with advanced algorithms, these systems now enable real-time therapeutic tailoring, improve medication adherence, and streamline clinical decision-making across diverse care settings. Verstraete et al[38] trained a machine-learning model on SUMMIT and IMPACT data to forecast treatment response, isolating a subgroup whose exacerbation rates fell by >53% when guided by lung-function and eosinophil biomarkers. VisionHealth and Boehringer Ingelheim[39] introduced the class IIaKata® app, whose AI-driven smartphone camera feedback corrects inhaler errors for ~75% of marketed devices, offering low-cost, home-based optimisation. Meanwhile, Mariani et al[40] deployed an end-to-end AutoML pipeline on Dutch primary-care EHRs, simultaneously differentiating asthma from COPD, predicting key clinical indices, and recommending personalised interventions while integrating seamlessly into existing health-information systems.

Additional significant contributions—including remote intelligent decision-support systems,[41] spirometry-based predictive models,[42] biomarker discovery for treatment stratification,[43] adverse-outcome prediction tools,[44] cost-effectiveness simulation models,[45] explainable clinical decision support systems,[46] and AI-assisted triage platforms[47] —are comprehensively summarized in Table 3. These innovations collectively represent the expanding landscape of AI-driven solutions for personalized COPD management, offering improved treatment precision, enhanced resource utilization, and greater accessibility to specialized care. Through these advancements, AI is transforming COPD treatment from a traditional trial-and-error approach to a data-driven, personalized paradigm that optimizes therapeutic outcomes while maximizing healthcare efficiency. The integration of these technologies into clinical workflows promises to revolutionize patient care while addressing the growing challenges of chronic disease management in diverse healthcare settings.

AI-Powered Pulmonary Rehabilitation and Long-Term Behavioral Management

Technical Foundations and Data Flows

Artificial intelligence is transforming pulmonary rehabilitation and long-term behavioral management in COPD by overcoming the spatial and temporal limitations of traditional center-based programs. Through personalized rehabilitation planning, remote exercise supervision, and behavioral interventions, AI—supported by wearable devices and mobile health technologies—shifts care from episodic clinical interactions to continuous, home-based management, significantly enhancing patients' quality of life and long-term outcomes.[4,70]

The foundation of AI-driven management lies in the integration of multisource dynamic data. Smartphones and wearable sensors continuously capture six key metrics: (1) activity capacity (eg, 6-minute walk distance via accelerometer/GPS);[71] (2) exercise intensity (heart rate variability, energy expenditure); (3) muscle function (isokinetic strength from smart devices);[72] (4) real-time symptom reporting (digital mMRC scores); (5) smoking cessation patterns (withdrawal symptoms and adherence); and (6) psychological state (digitized HADS scores).[73] These continuous, objective data streams provide the empirical basis for precision interventions.

Advancements in Clinical Evidence

Artificial intelligence is rapidly transforming pulmonary rehabilitation and long-term behavioural management for COPD by enabling continuous, home-based care through remote sensors, computer vision, and mobile platforms. These systems overcome traditional barriers of access and adherence by delivering personalised feedback and digital therapeutics in real time. Chen et al[48] deployed a deep-learning monitoring tool that achieved 97.5% accuracy in primary-care COPD management; combined with standardised therapy, it outperformed conventional care (80% accuracy) across lung function, blood gases, and symptom scores ($p < 0.05$). Jiang et al[55] tested a 12-week gamified HAPA-based remote programme in 159 patients, surpassing both usual remote rehabilitation and HAPA-only controls in adherence, quality of life, and psychological outcomes, with benefits persisting to 24 weeks. Tang et al[49] introduced a zero-contact RealSense/MediaPipe thoraco-abdominal tracker that strongly correlated chest-wall motion with spirometric volume ($r = 0.90$); real-time visual feedback increased chest excursion by 3 mm and lung volume by 0.28 L ($p < 0.05$), underscoring its suitability for unsupervised home rehabilitation.

Additional innovative approaches—including Respeck wearable sensors[51] camera-based exercise recognition systems,[52,54] multicentre tele-rehabilitation platforms,[53] health coaching interventions,[56] and speech biomarker analysis[57]—are comprehensively summarized in Table 4. These studies collectively illustrate the diverse and evolving landscape of AI-enabled pulmonary rehabilitation, highlighting trends toward non-contact monitoring, gamified engagement, and scalable home-based solutions.

Challenges and Countermeasures of AI in the Whole Process Management of COPD

Technical Challenges Faced

At present, the technical challenges confronting AI in whole-course COPD management mainly include: a) Data heterogeneity and lack of standardisation: physiological signals such as breath sounds, SpO_2, and HRV lack unified standards in acquisition devices, sampling frequency, and ambient-noise control, leading to cross-centre model-transfer difficulties and a 5–15% AUC drop in new settings; CT images differ in slice thickness, reconstruction algorithms, and dose, causing radiomic-feature drift that necessitates recalibration.[58] b) Small samples and data imbalance: acute exacerbations constitute only 5–10% of follow-up data, yielding models with high sensitivity but low specificity or requiring resampling that amplifies noise; low penetration of smart devices in older adults (23%) further shrinks training-set size.[74] c) Insufficient algorithmic explainability: deep models cannot provide clinically intelligible decision rationales when predicting exacerbations, reducing physician acceptance d) Compute-power and deployment bottlenecks: resource disparities between hospital PACS and wearable terminals mean that even compressed models may introduce 300–500 ms latency, hampering real-time alerting.[75]

Ethical and Social Challenges Faced

Ethical and social challenges for AI in whole-course COPD management chiefly encompass: a) Informed consent and data sovereignty: continuous physiological monitoring generates massive personal data; patients lack clear understanding of secondary use and cross-border transfer, risking trust crises.[76] b) Algorithmic bias and fairness: training sets predominantly comprise urban tertiary-hospital patients, under-representing rural and low-education groups, potentially skewing recommendations. c) Accountability: when AI alerts contradict clinicians' judgement and lead to missed diagnoses, no unified legal framework assigns liability among algorithm developers, hospitals, or physicians.[77] d) Technology access: poor digital perfusion in older adults impairs wearable SpO_2 accuracy; 47% struggle to operate smart apps, widening the digital divide.[74]

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Strategies for Overcoming Challenges

As shown in Figure 4, based on the research results, we have proposed a solution framework to address the obstacles and ethical challenges of trusted artificial intelligence technology in the management of chronic obstructive pulmonary disease.

Technical Dimension

Technical mitigation strategies include: a) Establish the COPDAI Data Standards Consortium: formulate minimum information checklists (MIADECOPD) for breath sounds, CT, and questionnaires, releasing open format-conversion scripts b) Federated learning + transfer learning: jointly train on multi-centre heterogeneous data under privacy protection, then fine-tune with small local datasets to address small-sample and domain-shift issues.[78] c) Explainable-AI toolchains: embed SHAP + LIME dual-interpretation frameworks in exacerbation-prediction models, outputting "key vital-sign contribution heat maps" for clinical verification. d) Edge–cloud co-architecture: lightweight CNNs extract features on wearables, deep analysis occurs in the cloud, balancing real-time performance and accuracy.[79]

Ethical and Social Dimension

Ethical and social mitigation strategies include: a) Tiered informed consent: three-layer consent forms for basic monitoring, secondary research use, and commercial purposes, all supporting withdrawal at any time. b) Fairness audits: every six months evaluate model sensitivity across age, sex, and education groups with an independent test set; retraining is triggered if disparity >10%.[80] c) Shared-liability insurance: hospitals, technology firms, and reinsurers jointly fund an "AI medical-liability pool", sharing compensation proportional to participation. d) Age-friendly design: voice interaction plus one-touch call functions reduce complexity; community AI-experience corners provide free training.[74]

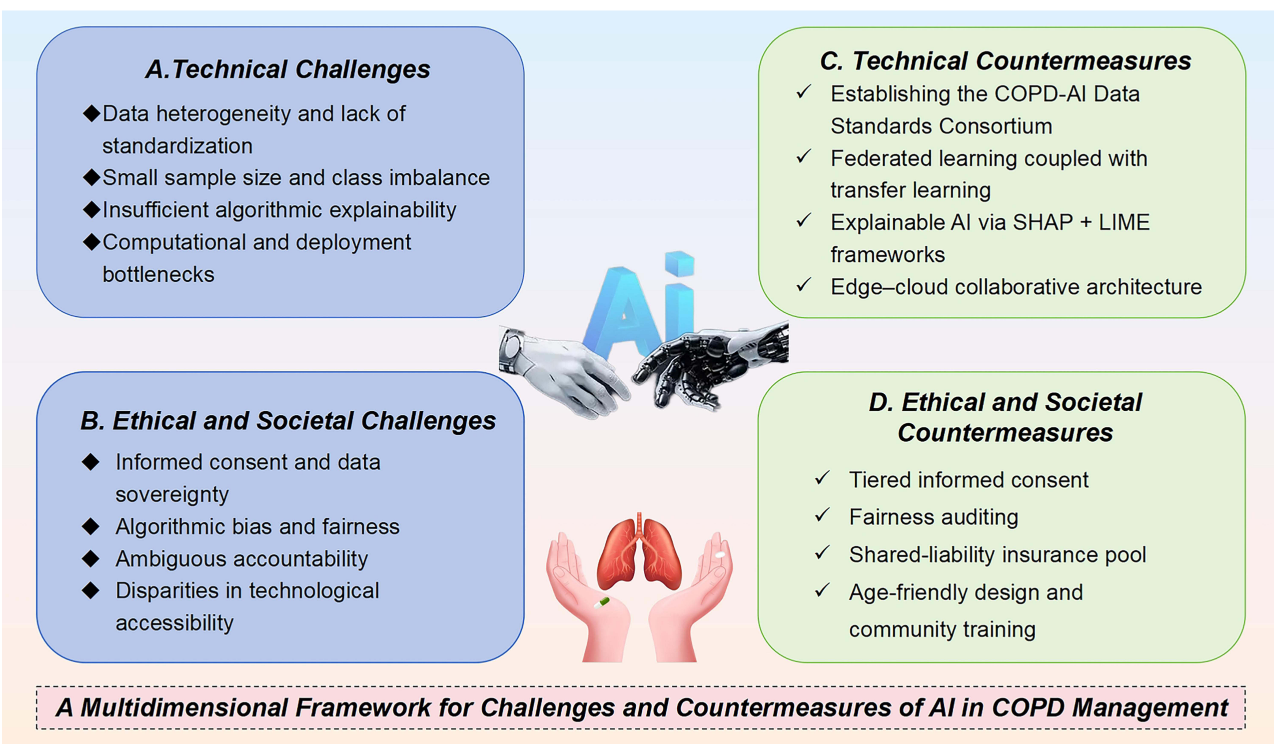

Figure 4 Toward Trustworthy AI in COPD Care: A Framework for Technical and Ethical Hurdles. This figure presents a multidimensional framework pairing major implementation barriers with targeted solutions. Technical challenges (eg, data heterogeneity) are addressed by countermeasures like federated learning (FL) and explainable AI (XAI). Ethical challenges (eg, algorithmic bias) are met with strategies such as fairness auditing and tiered consent, guiding the development of reliable and equitable AI systems.

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Discussion

Advantages and Limitations of AI in COPD Management

Artificial intelligence demonstrates significant potential across the COPD care continuum, with core advantages in three areas: (1) Prediction and early intervention: AI models (eg, XGBoost, LSTM) leveraging multisource data—wearable sensors, environmental APIs, and EHRs—improve exacerbation prediction (AUC >0.8), enabling 5–7-day early warnings and reducing readmissions by 25–48%.[18,24] Multi-omic models (eg, CatBoost) identify high-risk populations with 10-year prediction AUC of 0.81. (2) Diagnostic efficiency and personalization: AI-assisted tools (eg, CNN-based CT or spirometry analysis) achieve >90% accuracy, lowering misdiagnosis by 15–30%.[28,32,37] Treatment optimization via reinforcement learning and GNNs tailors therapies and reduces exacerbation risk by 53%.[38] (3) Resource optimization and access: AI-powered remote monitoring (eg, myCOPD) boosts rehabilitation adherence by >30% and cuts ED visits by 98%.[21,39,49]

Nevertheless, AI applications face notable limitations: (1) Limited generalizability: Model performance drops in cross-center validation (eg, radiomics AUC decrease of 0.08–0.12); data imbalance reduces specificity; [58,74,78] (2) Clinical integration challenges: Black-box decisions erode trust; heterogeneous data and hardware constraints hinder real-time use.[75] (3) Socio-ethical issues: Digital literacy gaps (47% among elderly), algorithmic bias, and data sovereignty concerns may worsen disparities.[74]

While the reported performance of AI models is promising, it is crucial to contextualize these findings within the limitations of the underlying evidence. As summarized in Tables 1–4, the included studies varied considerably in design and quality. Many were retrospective in nature and conducted in single centers, and a significant proportion lacked external validation, which may inflate performance estimates and limit generalizability. Furthermore, the predominance of observational studies introduces potential for confounding bias.

Future Research Directions

To overcome current limitations, future research should focus on: (1) Multimodal fusion and dynamic modelling: integrate multi-temporal data (breath sounds, air-pollution exposure, medication logs) to build a “digital-twin patient” platform that simulates long-term effects of intervention strategies (eg, QALY gains and hospitalisation costs).[44,45] (2) Explainable AI and causal reasoning: develop dual SHAP+LIME frameworks to enhance transparency (eg, “key-vital-sign heat maps” for exacerbation prediction) and combine reinforcement learning to generate auditable, individualised treatment pathways. (3) Cross-domain generalisation: advance federated learning for privacy-preserving multi-centre collaboration and apply transfer learning to address data-distribution shifts, improving model robustness in grassroots settings.[78] (4) Health-economics validation: design multi-centre RCTs to quantify the cost-effectiveness of AI-enabled whole-course management (eg, QALYs, direct medical costs) to provide evidence for reimbursement policy.[5,45]

Policy and Practice Recommendations

Scaling AI adoption in COPD management requires multi-stakeholder synergy: (1) Regulatory innovation: develop “Key Review Points for COPD AI Software”, specifying data-quality controls (eg, MIADECOPD standards), external validation, and dynamic-update cycles. (2) Payment reform: include “AI-assisted whole-course COPD management” in DRG add-on payments, incentivising healthcare institutions with 300–500 RMB per patient per year.[5,45] (3) Grassroots empowerment: establish “COPD AI Shared Hubs” within county medical communities to centrally procure compute and model services, lowering deployment costs;[74] develop age-friendly interfaces (voice interaction + one-touch call) and community AI-training corners to improve digital literacy. (4) Ethical governance: conduct biannual algorithmic-fairness audits (sensitivity disparities <10%) and create a tripartite “hospital–enterprise–insurance” shared-liability mechanism.[77,80]

Artificial intelligence is moving COPD care from “experience” to “data”. Gains in prediction, efficiency, and personalisation are clear, yet generalisability, explainability, and equity still limit bedside use. Embedding multimodal fusion, explainable AI, and federated learning within adaptive regulation and payment models is required to build a “prediction–prevention–personalisation” ecosystem that delivers precise, affordable COPD management worldwide.

Conclusions

This review systematically evaluates the transformative role of artificial intelligence (AI) across the full spectrum of COPD management. By synthesizing evidence from 40 studies, we demonstrate that AI models leveraging multimodal data within advanced computational frameworks can achieve AUCs >0.8 for tasks such as exacerbation prediction and personalized therapy, correlating with substantial reductions in hospital readmissions (25–48%) and emergency visits (up to 98%). These advancements significantly advance the 4P (Predictive, Preventive, Personalized, Participatory) medicine paradigm for COPD.

However, the promising results reported herein must be interpreted with caution. The effect sizes are primarily derived from specific, often research-oriented settings, and their generalizability to broader, more diverse populations requires further validation. Moreover, the clinical adoption of these technologies faces significant headwinds, including data heterogeneity, limited model explainability, the digital divide among elderly patients, and unresolved ethical concerns regarding data sovereignty and algorithmic bias. This review itself is subject to limitations, such as the heterogeneity of the included studies and potential publication bias, which future work with prospective registration and formal meta-analysis could address.

Ultimately, the translation of AI from research to routine practice is not automatic. It is conditional upon a concerted, multi-stakeholder effort. Future work must prioritize the development of cross-institutional data alliances, explainable AI systems, and robust digital twin platforms. Concurrently, policy support is indispensable, encompassing reimbursement reforms for AI-enabled care, the establishment of shared-computing infrastructures, and the promotion of age-friendly interfaces. Only by simultaneously addressing these technical, validation, and socio-ethical dimensions can we realize the full potential of AI to enable equitable and effective global access to precision COPD care.

Abbreviations

AI, Artificial Intelligence; AUC, Area Under the Receiver Operating Characteristic Curve; CNN, Convolutional Neural Network; DL, Deep Learning; EHR, Electronic Health Record; EMR, Electronic Medical Record; GBM, Gradient Boosting Machine; GNN, Graph Neural Network; LIME, Local Interpretable Model-agnostic Explanations; LSTM, Long Short-Term Memory; ML, Machine Learning; NLP, Natural Language Processing; RF, Random Forest; RL, Reinforcement Learning; SHAP, SHapley Additive exPlanations; SVM, Support Vector Machine; XAI, Explainable Artificial Intelligence; 6MWD, 6-Minute Walk Distance; ACC, Accelerometer; BMI, Body Mass Index; Borg, Borg Scale; CAT, COPD Assessment Test; EOS, Eosinophils; FEV_1, Forced Expiratory Volume in the first second; FVC, Forced Vital Capacity; HR, Heart Rate; HADS, Hospital Anxiety and Depression Scale; mMRC, modified Medical Research Council Dyspnea Scale; PRO, Patient-Reported Outcome; RR, Respiratory Rate; SpO_2, Peripheral Oxygen Saturation; AECOPD, Acute Exacerbation of Chronic Obstructive Pulmonary Disease; CDSS, Clinical Decision Support System; COPD, Chronic Obstructive Pulmonary Disease; GOLD, Global Initiative for Chronic Obstructive Lung Disease; PFT, Pulmonary Function Test; CT, Computed Tomography; CXR, Chest X-Ray; LAA, Low-Attenuation Area; WT, Wall Thickness; DRG, Diagnosis-Related Group; HAPA, Health Action Process Approach; HBPR, Home-Based Pulmonary Rehabilitation; ICS, Inhaled Corticosteroid; LABA, Long-Acting $Beta_2$-Agonist; LAMA, Long-Acting Muscarinic Antagonist; PR, Pulmonary Rehabilitation; QALY, Quality-Adjusted Life Year; RPM, Remote Patient Monitoring; FL, Federated Learning; GPS, Global Positioning System; IoMT, Internet of Medical Things; PHR, Personal Health Record.

Data Sharing Statement

All data used in this review are available via the databases PubMed, Web of Science and Embase, subject to the requisite subscription or access permissions. No original datasets were generated or analysed in the course of this study.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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