Am J Transl Res 2025;17(10):8087-8096
www.ajtr.org /ISSN:1943-8141/AJTR0166316

Original Article

Intelligent diagnosis and treatment model based on clinical data for home rehabilitation of chronic obstructive pulmonary disease

Fuguo Xue[1], Bin Zhu[1], Tingting Zhao[2], Youqin Chen[1]

[1]Department of Respiratory and Critical Care Medicine, Taizhou Cancer Hospital, Wenling 317502, Zhejiang, China; [2]Department of Respiratory and Critical Care Medicine, Zhuji Hospital Affiliated to Wenzhou Medical University, Zhuji 311800, Zhejiang, China

Received May 25, 2025; Accepted August 22, 2025; Epub October 15, 2025; Published October 30, 2025

Abstract: Objective: To evaluate the efficacy of a clinical data-driven intelligent diagnosis and treatment model in chronic obstructive pulmonary disease (COPD) home rehabilitation, focusing on improving patient outcomes through personalized interventions. Methods: A total of 82 COPD patients (control group) received conventional care from January to September 2023. An additional 86 patients (intelligent group) were managed via a cloud platform integrating wearable devices (smart bracelets, pulmonary function meters) and symptom tracking apps from October 2023 to July 2024. Real-time data (blood oxygen, heart rate, FEV1%, FVC) were uploaded daily, with long short-term memory -based acute exacerbation alerts. Personalized rehabilitation, medication, and nutrition guidance were delivered via mobile platforms, alongside biweekly video consultations. A 6-month follow-up assessed pulmonary function (FVC, FEV1%, MMEF, PEF), cardiac function (LVEDD, LVEF), 6MWD, dyspnea (mMRC), quality of life (SGRQ), compliance, and exacerbation events. Results: At 3-6 months, the intelligent group showed significant improvements in pulmonary function (higher FVC, FEV1%, MMEF, PEF; all $P < 0.05$), cardiac function (improved LVEDD, LVEF, 6MWD; all $P < 0.05$), symptoms (lower mMRC, SGRQ scores; both $P < 0.05$), and compliance (higher data upload and intervention response rates; both $P < 0.001$). Exacerbations were reduced, with fewer events and shorter hospitalizations (all $P < 0.05$). Conclusions: The intelligent model improves COPD rehabilitation through real-time monitoring and personalized care, significantly enhancing pulmonary and cardiac function, exercise capacity, and quality of life, while reducing exacerbations and hospitalizations. This model holds potential for broader clinical adoption.

Keywords: Clinical data intelligent diagnosis and treatment mode, chronic obstructive pulmonary disease, home-based rehabilitation management

Introduction

Chronic obstructive pulmonary disease (COPD) is the third leading cause of death worldwide, with its prevalence rising and disease burden increasing [1, 2]. According to the World Health Organization, there are approximately 384 million COPD patients globally, resulting in over 3 million deaths annually, with a prevalence rate of 13.7% among individuals aged 40 and above in China [3, 4]. Characterized by progressive airflow limitation, frequent acute exacerbations, and continuous lung function decline, COPD leads to repeated hospitalizations, impaired quality of life, and greater social and economic burdens [5-7]. The traditional hospital-centered diagnostic and treatment model primarily focuses on acute phase interventions but fails to address the stable phase, where dynamic tracking of symptoms and early risk warning is lacking [8, 9]. With an aging population and a shift in medical service models, home rehabilitation has become an essential component of COPD management. However, current home management approaches suffer from fragmented physiological data collection, delayed interventions, and lack of compliance monitoring [10, 11].

Recent advancements in artificial intelligence and clinical medicine offer new opportunities for chronic disease management. Wearable

https://doi.org/10.62347/EAOX7984

devices enable real-time monitoring of key physiological indicators like blood oxygen saturation and respiratory rate, which, when combined with structured data from lung function tests and medication records, create dynamic health profiles [12, 13]. Machine learning algorithms have demonstrated significant advantages in predicting disease progression, warning of acute exacerbations, and tailoring rehabilitation plans. Studies have shown that deep learning models have an AUC value of 0.87 for predicting the 30-day readmission risk in COPD patients [14, 15]. However, existing research mainly focuses on hospital-based decision-support systems, and the integration of intelligent diagnosis and treatment models in home environments faces challenges such as data integration, algorithm generalization, and doctor-patient collaboration mechanisms. Specifically, aligning clinical guidelines with the unique characteristics of home care remains unsolved.

This study aims to develop an intelligent diagnosis and treatment system based on multi-source clinical data, leveraging Internet of Things (IoT) sensors to capture real-time home environment parameters and patient physiological indicators. The system will incorporate a decision-making model with time-series analysis, overcoming the passive and reactive nature of traditional home management. It will establish a full-cycle management loop, including environmental risk alerts, dynamic rehabilitation adjustments, and intelligent medication reminders. The results will offer innovative solutions to enhance patient self-management, reduce acute exacerbations, and provide both theoretical and practical insights for developing intelligent chronic disease management systems.

Materials and methods

General information

Eighty-two COPD patients admitted to Taizhou Cancer Hospital from January to September 2023 were assigned to the control group, and 86 COPD patients admitted from October 2023 to July 2024 were assigned to the intelligent group. This study was approved by the Ethics Committee of Taizhou Cancer Hospital, and all procedures involving human participants were conducted in accordance with the Declaration of Helsinki (2013 revision).

Patient selection

Eligible patients met the following criteria: confirmed diagnosis of COPD according to the Global Initiative for Chronic Obstructive Lung Disease (GOLD) 2023 guidelines [16], with a post-bronchodilator forced expiratory volume in one second/forced vital capacity ratio < 0.70; age ≥ 40 years; COPD history of ≥ 2 years; clinical stability (no acute exacerbations requiring hospitalization or emergency care within the past 8 weeks); ability to operate basic digital interfaces (smartphone apps, wearable devices) after standardized training; and residence within a 30-km radius of the study center. Exclusion criteria included: severe respiratory comorbidities (e.g., active lung cancer, bronchiectasis with recurrent infections, untreated tuberculosis, interstitial lung disease); significant cognitive impairment (Mini-Mental State Examination score < 24) or psychiatric disorders; active malignancies or systemic autoimmune diseases; major organ dysfunction (hepatic failure, renal failure with estimated glomerular filtration rate < 30 mL/min/1.73 m^2, or New York Heart Association functional classification class III-IV heart failure); pregnancy or lactation; thoracic surgery or mechanical ventilation within 3 months prior to enrollment; inadequate home infrastructure (e.g., unstable internet, refusal to use monitoring equipment); planned relocation (> 4 weeks); severe visual/hearing impairment preventing device interaction; or concurrent enrollment in conflicting interventional trials.

Methods

The control group received standard management, including monthly outpatient follow-up, standardized health education manuals, basic medication guidance, and paper-based rehabilitation plans.

The intelligent group used an IoT + cloud computing-based intelligent diagnosis and treatment system. Patients uploaded data daily via a smart bracelet (monitoring blood oxygen, heart rate, and activity), a home pulmonary function meter (recording FEV1% and FVC), and a symptom self-assessment app (collecting

cough frequency, sputum characteristics, and COPD assessment test score elements). A dynamic prediction model based on the short-term memory neural network analyzed data trends in real time. If parameters deviated from baseline values by ≥ 15% or the acute exacerbation risk score exceeded a threshold, a three-level warning mechanism (platform alert, SMS to the attending physician, emergency contact notification) was triggered. Personalized rehabilitation plans, including respiratory training video guidance (with AI motion capture error correction), medication adjustments, and nutritional meal plans, were pushed to patients via mobile terminals. Additionally, at least biweekly video consultations were facilitated for two-way communication between doctors and patients. A decision tree rule base was established based on the GOLD guidelines, with parameter weights optimized every two weeks using machine learning algorithms.

Outcome measures

Pulmonary function: Pulmonary function was assessed using the CHEST AC-8800 pulmonary function tester (CHEST Company, Japan) before enrollment, and at 3 and 6 months post-enrollment. The following parameters were recorded: forced vital capacity (FVC), forced expiratory volume in one second as a (FEV1%), FEV1/FVC%, maximum mid-expiratory flow rate (MMEF), and peak expiratory flow rate (PEF).

Diaphragmatic function: The right diaphragmatic thickening fraction and diaphragmatic excursion were measured before enrollment, and at 3 and 6 months post-enrollment. Diaphragmatic excursion was defined as the vertical distance between the lowest point of the diaphragm (during expiration) and the highest point (during inspiration), measured under electrodialysis.

Cardiac function: Cardiac function was evaluated using the Philips IE33 echocardiography system before enrollment, and at 3 and 6 months post-enrollment. Key indices included left ventricular end-diastolic diameter (LVEDD) and left ventricular ejection fraction (LVEF).

Exercise endurance: Patients performed the 6-Minute Walk Test (6MWT) before enrollment, and at 3 and 6 months post-enrollment. A 30-meter flat, wide, and straight path was used, with patients instructed to walk as far as possible within 6 minutes. The distance walked during the first test was recorded, and after a 30-minute rest, a second test was performed. The distance from both tests was recorded, and the average distance was calculated.

Dyspnea evaluation: The modified Medical Research Council (mMRC) scale was used to assess dyspnea severity before enrollment, and at 3 and 6 months post-enrollment. Scores were as follows: 0, no dyspnea except after strenuous exercise; 1, shortness of breath when walking fast or climbing slowly; 2, walking slowly due to dyspnea; 3, walking 100 meters on level ground without resting; 4, dyspnea when dressing or undressing.

Quality of life: The St. George's Respiratory Questionnaire (SGRQ) [17] was used to evaluate quality of life before enrollment, and at 3 and 6 months post-enrollment. The questionnaire consists of 51 items across three dimensions: disease impact, activity limitation, and respiratory symptoms. Scores range from 0 to 100, with higher scores indicating worse quality of life. The scale demonstrated good internal consistency (Cronbach's $\alpha = 0.88$).

Statistical analysis

Statistical analyses were performed using SPSS version 29.0 (IBM Corp., Armonk, NY). Continuous variables were first tested for normality using the Shapiro-Wilk test and visual inspection of Q-Q plots. Normally distributed data were expressed as mean ± standard deviation. Between-group comparisons were performed using independent samples t-tests for two groups, and one-way ANOVA for comparisons involving more than two groups. For longitudinal changes within groups at multiple time points, repeated measures ANOVA followed by Tukey's HSD test was used. Categorical variables were presented as frequencies (percentages) and compared using χ^2 or Fisher's exact tests when expected cell counts were < 5. A two-tailed *P*-value of < 0.05 was considered statistically significant.

Results

Comparison of clinical data

The baseline clinical characteristics of the two groups were comparable, with no significant differences observed across the following parameters: gender distribution (male/female), mean age, body mass index, duration of COPD,

Table 1. Comparison of clinical data between the two groups

Clinical data	Control group (n = 82)	Intelligent group (n = 86)	t/χ^2	P
Gender				
Male	49	54	0.163	0.686
Female	33	32		
Age (years, $\bar{x}$ ± sd)	68.4 ± 11.5	69.7 ± 11.0	0.758	0.450
BMI (kg/m^2, $\bar{x}$ ± sd)	23.97 ± 2.16	24.05 ± 2.31	0.232	0.817
Duration (years, $\bar{x}$ ± sd)	6.93 ± 2.53	6.59 ± 1.75	1.017	0.311
Level of education				
Junior high school and below	46	53	0.989	0.320
High school and above	39	33		
Smoking history				
Yes	30	27	0.504	0.478
No	52	59		
hypertension				
Yes	19	22	0.132	0.716
No	63	64		
diabetes				
Yes	14	12	0.312	0.576
No	68	74		
GOLD grading				
Grades I to II	54	56	0.010	0.920
Grades III to IV	28	30		

education level (junior high school or below vs. high school or above), smoking history (yes/no), comorbidities (hypertension and diabetes; yes/no), and GOLD disease severity grading (grades I-II vs. III-IV). All comparisons yielded *P*-values > 0.05, confirming homogeneity of the cohorts before intervention, as shown in **Table 1**.

Comparison of pulmonary function indexes

Pre-intervention pulmonary function measurements (FVC, FEV1%, FEV1/FVC%, MMEF, PEF) showed no significant between-group differences (all P > 0.05). At 3 and 6 months after enrollment, pulmonary function indexes (FVC, FEV1%, FEV1/FVC%, MMEF, and PEF) in both groups were significantly higher than those at baseline (all P < 0.05). The intelligent group exhibited significantly better pulmonary function than the control group at 3 and 6 months post-enrollment (all P < 0.05), as shown in **Figure 1**.

Comparison of diaphragmatic function

Baseline right diaphragmatic thickening fraction and diaphragmatic mobility were comparable between groups (both P > 0.05). At 3 and 6 months, both diaphragmatic thickening fraction and mobility were significantly improved in both groups (both P < 0.05). The intelligent group showed significantly better results than the control group at 3 and 6 months (both P < 0.05), as shown in **Figure 2**.

Comparison of cardiac function and exercise endurance

Initial assessments revealed no significant differences in cardiac function (LVEDD, LVEF) or exercise capacity (6MWD) between groups (all P > 0.05). After 3 and 6 months, the intelligent group demonstrated significantly better cardiac function and exercise endurance compared to baseline and the control group (all P < 0.05), as shown in **Figure 3**.

Comparison of dyspnea scores

Pre-intervention mMRC dyspnea scores showed no significant difference between the groups (P > 0.05). At 3 and 6 months, both groups had significantly lower mMRC scores than those at baseline (P < 0.05). The intelligent group showed significantly lower mMRC scores com-

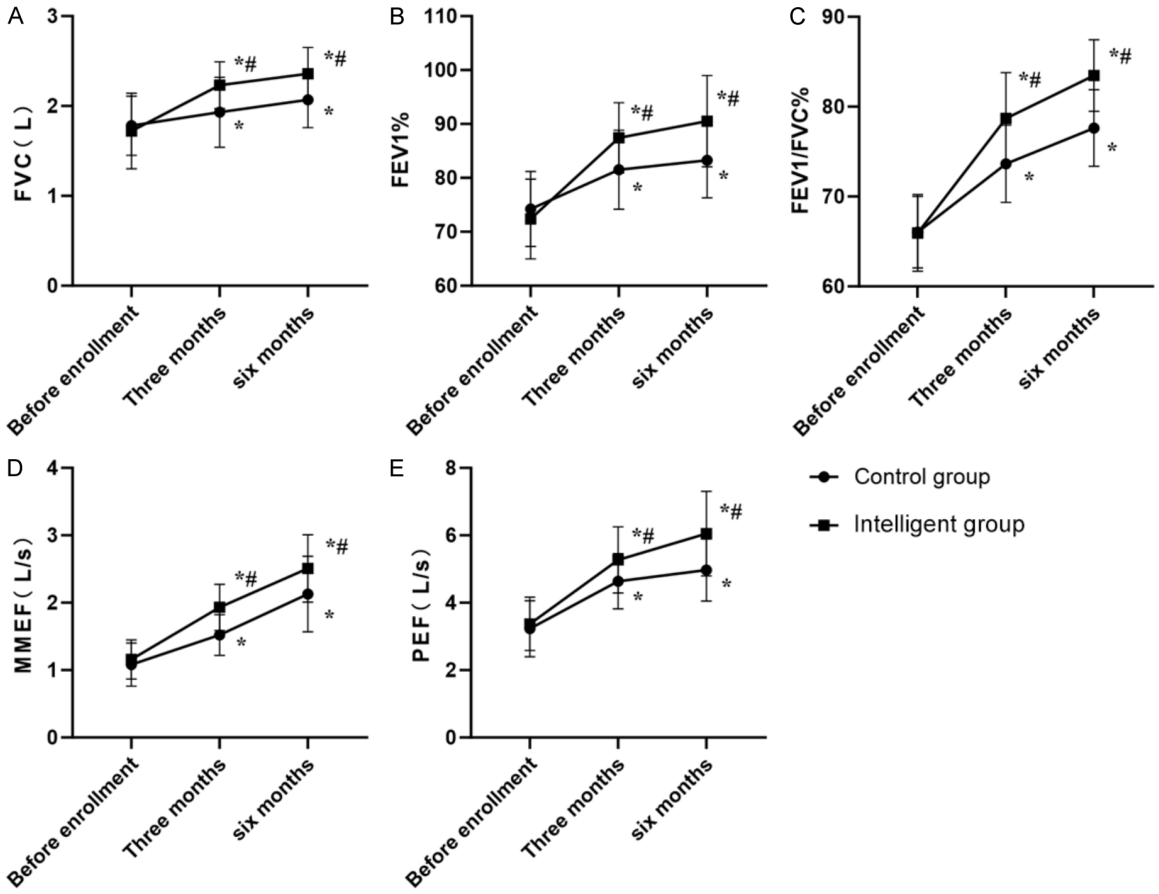

Figure 1. Changes in pulmonary function indexes in the two groups. A. FVC; B. FEV1%; C. FEV1/FVC%; D. MMEF; E. PEF. Note: Compared with before enrollment, *P < 0.05; Compared with the control group at the same period, #P < 0.05. FVC: forced vital capacity; FEV1%: forced expiratory volume in one second; MMEF: maximum mid-expiratory flow rate; PEF: peak expiratory flow rate.

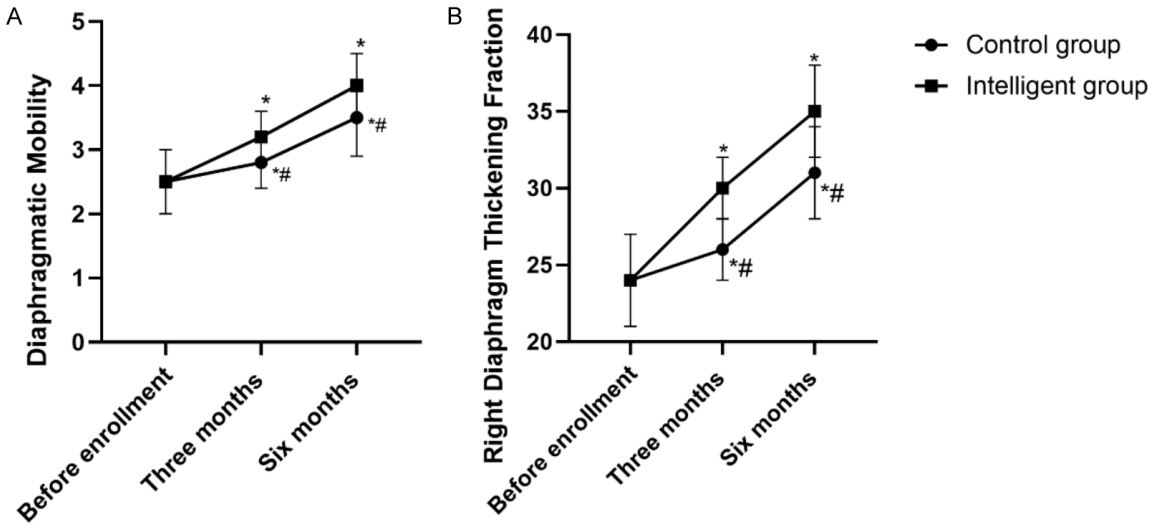

Figure 2. Comparison of diaphragmatic function between the two groups. A. Diaphragmatic mobility; B. Right diaphragmatic thickening fraction. Note: Compared with before enrollment, *P < 0.05; Compared with the control group at the same period, #P < 0.05.

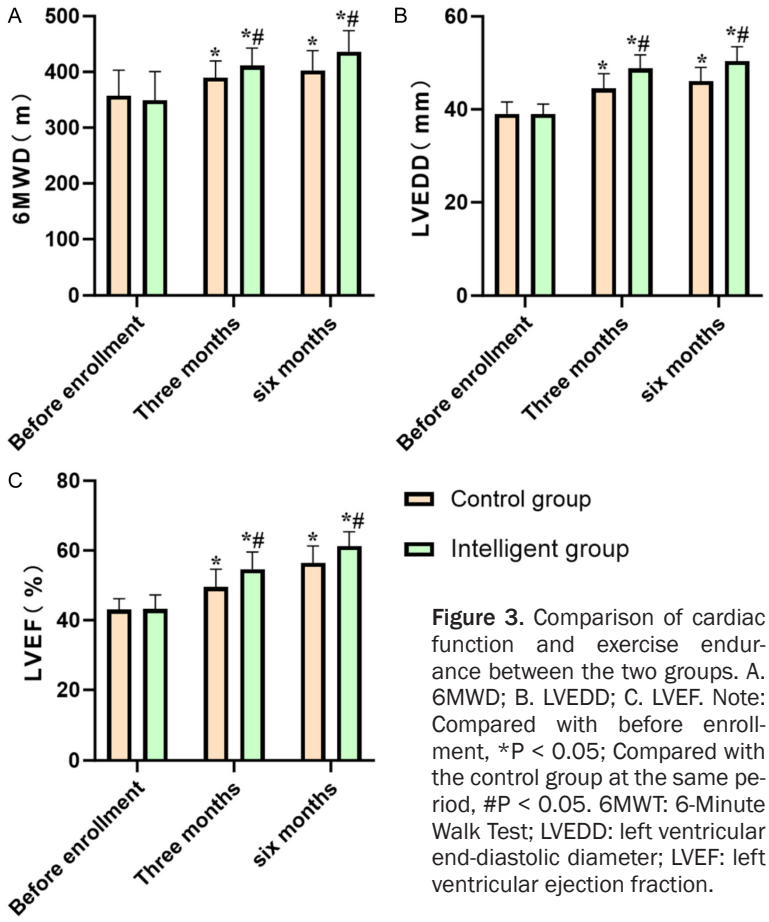

Figure 3. Comparison of cardiac function and exercise endurance between the two groups. A. 6MWD; B. LVEDD; C. LVEF. Note: Compared with before enrollment, *P < 0.05; Compared with the control group at the same period, #P < 0.05. 6MWT: 6-Minute Walk Test; LVEDD: left ventricular end-diastolic diameter; LVEF: left ventricular ejection fraction.

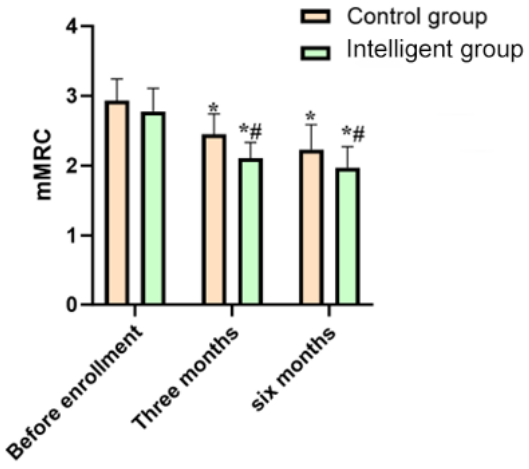

Figure 4. Comparison of mMRC scores between the two groups. Note: Compared with before enrollment, *P < 0.05; Compared with the control group at the same period, #P < 0.05. mMRC: modified Medical Research Council.

pared to the control group at both 3 and 6 months (P < 0.05), as shown in **Figure 4**.

Comparison of quality of life

Baseline SGRQ scores across all dimensions (respiratory symptoms, activity limitation, disease impact) were comparable between the groups (all P > 0.05). As shown in **Figure 5**, both groups demonstrated a decreasing trend in respiratory symptoms, activity limitation, and disease impact over time (all P < 0.05). The intelligent group consistently showed greater improvement in these areas compared to the control group, as depicted in **Figure 5** (all P < 0.05).

Comparison of patient compliance and system usage

The daily data upload rate was significantly higher in the intelligent group (t = 12.345, P < 0.001). Similarly, the intervention response rate (t = 10.123, P < 0.001) and doctor-patient interaction frequency (t = 14.567, P < 0.001) were higher in the intelligent group. However, the difference in the number of non-compliant patients (12 vs. 8) was not statistically significant (χ^2 = 1.987, P = 0.159), as shown in **Table 2**.

Comparison of exacerbation events and hospitalization outcomes

The total number of exacerbation events was significantly lower in the intelligent group (χ^2 = 5.678, P = 0.017), as was the number of severe exacerbations (χ^2 = 4.321, P = 0.037). The intelligent group also had significantly fewer hospitalizations (χ^2 = 4.890, P = 0.027) and shorter average hospitalization days (t = 3.456, P = 0.001), as shown in **Table 3**.

Discussion

With an aging population and persistent air pollution, COPD has become a significant global public health challenge [18-20]. The disease is characterized by persistent airflow limitation, progressive lung function decline, and repeat-

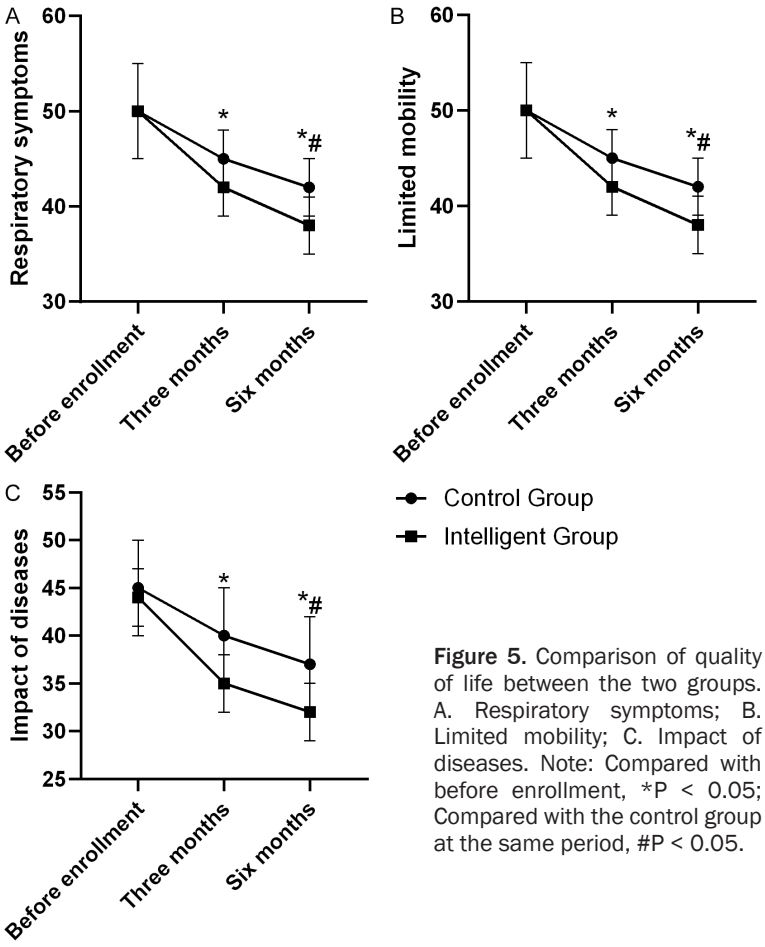

Figure 5. Comparison of quality of life between the two groups. A. Respiratory symptoms; B. Limited mobility; C. Impact of diseases. Note: Compared with before enrollment, *P < 0.05; Compared with the control group at the same period, #P < 0.05.

ed acute exacerbations, severely affecting patients' quality of life and imposing a substantial medical and economic burden [21-23]. The traditional home-based rehabilitation model relies on regular outpatient follow-ups and subjective symptom reports, resulting in fragmented data collection and delayed interventions, which complicates accurate and dynamic disease management [24-26]. In recent years, the integration of the Internet of Things, cloud computing, and machine learning technologies has provided new strategies to overcome these challenges. By combining wearable devices, intelligent terminals, and clinical data, a real-time monitoring, intelligent warning, and dynamic intervention system has emerged as a key approach to enhance COPD management efficiency [27-29]. This study explores the application of intelligent diagnosis and treatment modes based on clinical data in home settings, aiming to provide an empirical foundation for optimizing disease management.

The results of this study demonstrated that the intelligent group outperformed the traditional management model in improving lung function, exercise tolerance, and quality of life. Continuous improvements in lung function indices (FVC, FEV1%, and MMEF) confirm that the intelligent system detects early changes in small airway function through daily monitoring and trend analysis, enabling timely adjustments to bronchodilator use and delaying airflow limitation progression [30, 31]. The significant improvement in 6-minute walk distance (6MWD) may be attributed to the personalized training program, which adapts based on real-time exercise data. For instance, the system reduces exercise intensity when blood oxygen fluctuations are detected or increases the training load incrementally as muscle strength improves. This dynamic adaptation is more physiologically appropriate than the traditional fixed rehabilitation programs [32, 33]. The decrease in mMRC scores reflects the advantages of multi-dimensional symptom monitoring. By integrating data such as cough frequency, sputum characteristics, and blood oxygen levels, the system can identify silent dyspnea early, initiate appropriate interventions (e.g., atomization inhalation, postural expectoration guidance), and prevent delays in symptom management. The improvement in SGRQ scores across activity limitation, respiratory symptoms, and social psychology highlights the system's ability to address the limitations of the traditional biomedical model by providing interdisciplinary interventions, such as psychological counseling and AI-driven nutritional guidance [34, 35].

However, this study has several limitations. First, while the inclusion criteria followed the GOLD guidelines, the study sample was drawn from a single medical center, which may introduce homogeneity bias due to regional differ-

Table 2. Comparison of patient compliance and system usage between the two groups

Index	Control Group (n = 82)	Intelligent Group (n = 86)	t/χ^2 Value	*P*-value
Daily data upload rate (%)	42.32 ± 12.12	91.72 ± 6.81	12.345	< 0.001
Intervention response rate (%)	35.01 ± 8.20	82.53 ± 5.33	10.123	< 0.001
Doctor-patient interaction frequency (times/week)	0.52 ± 0.21	2.84 ± 0.73	14.567	< 0.001
Non-compliant patients (n)	12	8	1.987	0.154

Table 3. Comparison of exacerbation events between the two groups

Index	Control Group (n = 82)	Intelligent Group (n = 86)	t/χ^2 Value	*P*-value
Total exacerbation events	18	9	5.678	0.017
Severe exacerbation events	6	2	4.321	0.037
Hospitalization cases	12	5	4.890	0.027
Average hospitalization days (days)	4.21 ± 1.52	2.80 ± 1.23	3.456	0.001

ences in medical standards and patient education. Multi-center studies are needed to validate the generalizability of the findings. Second, although the 6-month follow-up period provides insights into the short-term effects, COPD is a chronic, lifelong disease. Long-term follow-up (3-5 years) is needed to evaluate the sustained impact on acute exacerbation frequency, annual lung function decline, and other long-term indicators. Additionally, challenges related to elderly patients' ability to operate smart devices were not fully addressed; 8 cases of non-compliance due to complex interfaces suggest that further simplification of the human-computer interface and enhanced user training are required.

In conclusion, the intelligent diagnosis and treatment model based on clinical data enables dynamic monitoring of vital signs through IoT technology, establishes individualized warning thresholds via machine learning algorithms, and combines guideline-driven, stepwise intervention strategies to form a closed-loop COPD home rehabilitation management system. This model effectively improves cardiopulmonary function, enhances exercise endurance, and improves quality of life. Its core value lies in transforming passive care into active health management and reducing medical resource consumption through data-driven, precise interventions. Future research should focus on integrating new technologies, such as 5G telemedicine and digital twins, while expanding sample representation, addressing medical ethics, and ensuring data security. This will support the transition of intelligent diagnosis and treatment models from technical innovation to clinical practice, ultimately achieving a paradigm shift in COPD full-cycle health management.

Acknowledgements

This work was supported by Zhejiang Province City and County Science and Technology Plan Project (XM20240693).

Disclosure of conflict of interest

None.

Address correspondence to: Youqin Chen, Department of Respiratory and Critical Care Medicine, Taizhou Cancer Hospital, No. 50 Zhenxin Road, Xinhe Town, Wenling 317502, Zhejiang, China. Tel: +86-15868625826; E-mail: chenyouqin826@sina.com

References

[1] Ritchie AI and Wedzicha JA. Definition, causes, pathogenesis, and consequences of chronic obstructive pulmonary disease exacerbations. Clin Chest Med 2020; 41: 421-438.

[2] Yang IA, Jenkins CR and Salvi SS. Chronic obstructive pulmonary disease in never-smokers: risk factors, pathogenesis, and implications for prevention and treatment. Lancet Respir Med 2022; 10: 497-511.

[3] Marti JD, McWilliams D and Gimeno-Santos E. Physical therapy and rehabilitation in chronic obstructive pulmonary disease patients admitted to the intensive care unit. Semin Respir Crit Care Med 2020; 41: 886-898.

[4] Qian Y, Cai C, Sun M, Lv D and Zhao Y. Analyses of factors associated with acute exacerbations of chronic obstructive pulmonary disease: a review. Int J Chron Obstruct Pulmon Dis 2023; 18: 2707-2723.
[5] Adrish M, Anand MP and Hanania NA. Phenotypes of asthma-chronic obstructive pulmonary disease overlap. Immunol Allergy Clin North Am 2022; 42: 645-655.
[6] Shao KM and Bernstein JA. Asthma-chronic obstructive pulmonary disease overlap: the role for allergy. Immunol Allergy Clin North Am 2022; 42: 591-600.
[7] Brassington K, Selemidis S, Bozinovski S and Vlahos R. Chronic obstructive pulmonary disease and atherosclerosis: common mechanisms and novel therapeutics. Clin Sci (Lond) 2022; 136: 405-423.
[8] Mathioudakis AG, Janssens W, Sivapalan P, Singanayagam A, Dransfield MT, Jensen JS and Vestbo J. Acute exacerbations of chronic obstructive pulmonary disease: in search of diagnostic biomarkers and treatable traits. Thorax 2020; 75: 520-527.
[9] Wang Q and Liu S. The effects and pathogenesis of PM2.5 and its components on chronic obstructive pulmonary disease. Int J Chron Obstruct Pulmon Dis 2023; 18: 493-506.
[10] Jeyachandran V and Hurst JR. Advances in chronic obstructive pulmonary disease: management of exacerbations. Br J Hosp Med (Lond) 2022; 83: 1-7.
[11] Lee AHY, Snowden CP, Hopkinson NS and Pattinson KTS. Pre-operative optimisation for chronic obstructive pulmonary disease: a narrative review. Anaesthesia 2021; 76: 681-694.
[12] Sobala R and De Soyza A. Bronchiectasis and chronic obstructive pulmonary disease overlap syndrome. Clin Chest Med 2022; 43: 61-70.
[13] O'Neill E, Ryan S and McNicholas WT. Chronic obstructive pulmonary disease and obstructive sleep apnoea overlap: co-existence, comorbidity, or causality? Curr Opin Pulm Med 2022; 28: 543-551.
[14] Mkorombindo T and Dransfield MT. Pre-chronic obstructive pulmonary disease: a pathophysiologic process or an opinion term? Curr Opin Pulm Med 2022; 28: 109-114.
[15] Guthrie A. Chronic obstructive pulmonary disease series part 4: identifying, managing, and preventing exacerbations. Sr Care Pharm 2023; 38: 361-369.
[16] Criner G and Duffy S. Reducing and managing chronic obstructive pulmonary disease exacerbations with tiotropium + olodaterol. Curr Med Res Opin 2021; 37: 275-284.
[17] Wang Z, Locantore N, Haldar K, Ramsheh MY, Beech AS, Ma W, Brown JR, Tal-Singer R, Barer MR, Bafadhel M, Donaldson GC, Wedzicha JA, Singh D, Wilkinson TMA, Miller BE and Brightling CE. Inflammatory endotype-associated airway microbiome in chronic obstructive pulmonary disease clinical stability and exacerbations: a multicohort longitudinal analysis. Am J Respir Crit Care Med 2021; 203: 1488-1502.
[18] Baou K, Katsi V, Makris T and Tousoulis D. Beta blockers and chronic obstructive pulmonary disease (COPD): sum of evidence. Curr Hypertens Rev 2021; 17: 196-206.
[19] Peng C, Yan Y, Li Z, Jiang Y and Cai Y. Chronic obstructive pulmonary disease caused by inhalation of dust: a meta-analysis. Medicine (Baltimore) 2020; 99: e21908.
[20] Libu C, Otelea MR, Arghir IA, Rascu A, Antoniu SA and Arghir OC. Challenges in diagnosing occupational chronic obstructive pulmonary disease. Medicina (Kaunas) 2021; 57: 911.
[21] Leduc-Gaudet JP and Hussain SNA. Muscle wasting in chronic obstructive pulmonary disease: not enough autophagy? Am J Respir Cell Mol Biol 2022; 66: 587-588.
[22] Yawn BP, Leidy NK and Martinez F. Screening for chronic obstructive pulmonary disease: unmet needs and future considerations. JAMA 2022; 327: 126-128.
[23] Boulet LP and Hanania NA. When asthma and chronic obstructive pulmonary disease overlap; Current knowledge and unmet needs. Immunol Allergy Clin North Am 2022; 42: 499-505.
[24] Penuelas O, Frutos-Vivar F and Mancebo J. Invasive mechanical ventilation in chronic obstructive pulmonary disease exacerbations. Semin Respir Crit Care Med 2020; 41: 798-805.
[25] Almagro P, Boixeda R, Diez-Manglano J, Gomez-Antunez M, Lopez-Garcia F and Recio J. Insights into chronic obstructive pulmonary disease as critical risk factor for cardiovascular disease. Int J Chron Obstruct Pulmon Dis 2020; 15: 755-764.
[26] Hahn DL. Does the asthma-chronic obstructive pulmonary disease overlap syndrome (ACOS) exist? A narrative review from epidemiology and practice. Allergol Immunopathol (Madr) 2022; 50: 100-106.
[27] Kazeminasab S, Emamalizadeh B, Jouyban A, Shoja MM and Khoubnasabjafari M. Macromolecular biomarkers of chronic obstructive pulmonary disease in exhaled breath condensate. Biomark Med 2020; 14: 1047-1063.
[28] Ramadan F. Optimising chronic obstructive pulmonary disease care: an overview for the community nurse. Br J Community Nurs 2024; 29: 352-353.
[29] Ramalho SHR and de Albuquerque ALP. Chronic obstructive pulmonary disease in heart failure: challenges in diagnosis and treatment for

HFpEF and HFrEF. Curr Heart Fail Rep 2024; 21: 163-173.
[30] Czarnota P, MacLeod JL, Gupta N, Manichaikul A and Shim YM. Sex differences in chronic obstructive pulmonary disease: implications for pathogenesis, diagnosis, and treatment. Int J Mol Sci 2025; 26: 2747.
[31] Thomson NC. The role of smoking in asthma and chronic obstructive pulmonary disease overlap. Immunol Allergy Clin North Am 2022; 42: 615-630.
[32] Singh D. A new treatment for chronic obstructive pulmonary disease: ensifentrine moves closer. Am J Respir Crit Care Med 2023; 208: 344-346.
[33] Polverino F and Kalhan R. Leveraging omics to predict chronic obstructive pulmonary disease exacerbations: the "immunome". Am J Respir Crit Care Med 2023; 208: 220-222.
[34] Yawn BP, Mintz ML and Doherty DE. GOLD in practice: chronic obstructive pulmonary disease treatment and management in the primary care setting. Int J Chron Obstruct Pulmon Dis 2021; 16: 289-299.
[35] De Luca SN and Vlahos R. Targeting accelerated pulmonary ageing to treat chronic obstructive pulmonary disease-induced neuropathological comorbidities. Br J Pharmacol 2024; 181: 3-20.