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REVIEW

The Role of Computed Tomography and Artificial Intelligence in Evaluating the Comorbidities of Chronic Obstructive Pulmonary Disease: A One-Stop CT Scanning for Lung Cancer Screening

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Abstract: Chronic obstructive pulmonary disease (COPD) is a major cause of morbidity and mortality worldwide. Comorbidities in patients with COPD significantly increase morbidity, mortality, and healthcare costs, posing a significant burden on the management of COPD. Given the complex clinical manifestations and varying severity of COPD comorbidities, accurate diagnosis and evaluation are particularly important in selecting appropriate treatment options. With the development of medical imaging technology, AI-based chest CT, as a noninvasive imaging modality, provides a detailed assessment of COPD comorbidities. Recent studies have shown that certain radiographic features on chest CT can be used as alternative markers of comorbidities in COPD patients. CT-based radiomics features provided incremental predictive value than clinical risk factors only, predicting an AUC of 0.73 for COPD combined with CVD. However, AI has inherent limitations such as lack of interpretability, and further research is needed to improve them. This review evaluates the progress of AI technology combined with chest CT imaging in COPD comorbidities, including lung cancer, cardiovascular disease, osteoporosis, sarcopenia, excess adipose depots, and pulmonary hypertension, with the aim of improving the understanding of imaging and the management of COPD comorbidities for the purpose of improving disease screening, efficacy assessment, and prognostic evaluation.

Keywords: chronic obstructive pulmonary disease, COPD, cardiovascular disease, CVD, lung cancer, osteoporosis, computed tomography, CT

Introduction

Chronic obstructive pulmonary disease (COPD) ranks as the third most common cause of death globally, distinguished by its progressive and irreversible airflow restriction.[1] Economically, the disease imposes a heavy burden on health care, with billions of dollars in direct medical costs and productivity losses annually.[2] Although COPD mainly affects the lungs, it is a complex multicomponent disease characterized by chronic systemic inflammation, which often coexists with other diseases, called comorbidities, mainly including lung cancer, cardiovascular disease (CVD), osteoporosis, and so on. The underlying mechanisms of COPD and its comorbidities remain incompletely understood.[3] Notably, the risk of hospitalization and mortality in patients with COPD is closely related to its comorbidities, and the risk of some comorbidities increases with the frequency of acute exacerbations of COPD.[4,5] There is some positive feedback between the two. In China, the prevalence of COPD in adults over 40 years of age is 13.7%, but the disease awareness rate is less than 1%, and there is a large blind spot in the publicity and management of COPD comorbidities.[6,7]

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Due to the high prevalence and negative impact of comorbidities in the COPD population, effective screening and management can improve outcomes and quality of life in the disease population. COPD disease management strategies fail to provide clear recommendations on how to assess and manage comorbidities.[3] The current gold standard for diagnosing and evaluating COPD is the pulmonary function test (PFT).[8] Yet, PFT can only reflect the global lung function changes in COPD patients, not the focal changes and comorbidities. In recent years, advanced imaging techniques—including cardiac MRI and Single Photon Emission Computed Tomography (SPECT)—have been widely adopted for assessing COPD-related complications such as cardiovascular disease (CVD) and lung cancer. However, their clinical utility is constrained by significant limitations, notably prolonged scan durations and high costs.[9,10] In the era of large-scale lung cancer screening (LCS), chest CT, which can locate and characterize the pathological abnormalities of chest diseases, has a high prevalence rate in major diseases.[11] As a non-invasive tool, CT is of great clinical value in the early diagnosis, monitoring, and follow-up of diseases in primary medical units. It can be used for long-term disease management of COPD comorbidities and maximize cost-effectiveness with promising one-stop scanning.

Artificial Intelligence (AI) is the technology that displays human intelligence through computer programs, capable of using algorithms to analyze a large amount of reliable data, automatically learning the hidden information in the data, and making predictions about unknown events in the real world.[12] The application of AI-based systems has been reported to excel in early screening, staged diagnosis, and prognosis of many chest diseases while reducing the workload of radiologists and maintaining diagnostic accuracy.[13–17] As AI technology leveraging CT imaging progresses rapidly, CT has emerged as a highly potent and widely utilized diagnostic tool, offering immense promise in identifying and managing COPD comorbidities. Especially in the absence of standardized screening guidelines, the integration of AI-based tools would be helpful. However, data bias and model generalizability make AI challenging that need to be validated by in-depth research.[18] In this paper, we have conducted a comprehensive review of the research progress on various comorbidities of COPD, including lung cancer, CVD, osteoporosis, sarcopenia, excess adipose depots, and pulmonary hypertension, from the perspectives of CT and AI. Research on the application of CT in COPD comorbidities is shown in Table 1.

Table 1 Research on the Application of CT in COPD Comorbidities

References	Year of Publication	First Author	COPD Comorbidities	Composition of the Sample Population	Methodologies
[19]	2024	Mahajan A	Lung cancer	223 participants (143 male and 76 female)	Deep-learning-based CT radiogenomic models and radiomic signatures
[20]	2024	Long Jiang	Lung cancer	355 participants (127 male and 228 female)	Quantitative CT
[21]	2025	Runhuang Yang	Lung cancer	796 participants (496 male and 300 female)	CT-Based deep learning model
[22]	2024	Wenjia Zhang	Lung cancer	527 participants (313 male and 214 female)	CT characteristics of lung nodules
[23]	2024	Chengdi Wang	Lung cancer	45064 participants	CT-Based China-Lung-RADS pipeline
[24]	2023	TaoHu Zhou	Lung cancer	498 participants (149 male and 349 female)	CT-Based radiomic nomogram
[25]	2024	Anna M Marcinkiewicz	Lung cancer	24401 participants (14468 male and 9933 female)	CT-Based machine learning
[26]	2018	Surya P Bhatt	Cardiovascular disease	1875 participants (14468 male and 9933 female)	Agatston and Weston scores
[27]	2024	Anne Marie Augustin	Cardiovascular disease	39 participants	Photon-Counting detector CT
[28]	2024	Bangjun Guo	Cardiovascular disease	5297 participants (3178 male and 2119 female)	Coronary CT-derived fractional flow reserve

(*Continued*)

Table 1 (Continued).

References	Year of Publication	First Author	COPD Comorbidities	Composition of the Sample Population	Methodologies
[29]	2024	Martin Soschynski	Cardiovascular disease	105 participants (68 male and 37 female)	CT-derived fractional flow reserve and dynamic CT myocardial perfusion imaging
[30]	2024	XiaoQing Lin	Cardiovascular disease	976 participants (799 male and 177 female)	CT-based whole lung radiomics
[31]	2025	XiaoQing Lin	Cardiovascular disease	686 participants (556 male and 130 female)	CT-Based radiomics nomogram of lung and mediastinal features
[32]	2022	Laura Zajančkauskienė	Cardiovascular disease	133 participants with low to intermediate risk of coronary artery disease and 194 intermediate stenosis of coronary artery disease	A semi-automated cardiac computed tomography angiography atherosclerotic plaque analysis program
[33]	2024	Nick S Nurmohamed	Cardiovascular disease	536 participants (297 male and 239 female)	Artificial intelligence-guided quantitative coronary computed tomography angiography analysis
[34]	2025	Heqi Yang	Osteoporosis	284 participants (208 male and 76 female)	CT-Based fracture risk prediction model
[35]	2024	Danica Vuković	Osteoporosis	200 participants (134 male and 66 female)	Type and grade of emphysema
[36]	2018	Jessica Bon	Osteoporosis	240 participants (126 male and 114 female)	CT-based visually assessed emphysema
[37]	2018	Kenichi Goto	Osteoporosis	103 participants (7 male and 96 female)	Extent of emphysematous lesions
[38]	2024	Xiaoliu Zhang	Osteoporosis	100 participants	Deep learning combined with shape model and finite element analysis
[39]	2024	Syed Ahmed Nadeem	Osteoporosis	40,050 vertebrae from 3231 COPDGene participants	Chest CT-based artificial intelligence and morphologic features
[40]	2021	Farhad Pishgar	Excess adipose depots	2994 participants (1443 male and 1551 female)	Soft-tissue markers subcutaneous adipose tissue, intermuscular adipose tissue, and pectoralis muscle index from chest CT
[41]	2022	Xin Qiao	Sarcopenia	103 participants (156 male and 19 female)	CT-derived pectoralis muscle cross-sectional area and pectoralis muscle attenuation
[42]	2024	Ji Wu	Excess adipose depots	1150 participants (754 male and 396 female)	High visceral adipose tissue area from chest CT
[43]	2024	Jae-Kyeong Lee	Pulmonary hypertension	435 participants (369 male and 66 female)	Pulmonary artery-to-aorta
[44]	2017	Natalie Terzikhan	Pulmonary hypertension	2197 participants (1070 male and 1127 female)	Pulmonary artery-to-aorta

Abbreviation: COPD, chronic obstructive pulmonary disease.

COPD and Lung Cancer

Many patients with lung cancer have a history of COPD.[45] Lung cancer is a common complication of COPD, while COPD is considered an important risk factor for lung cancer.[46,47] COPD and lung cancer share common risk factors such as tobacco intake, DNA damage pathways, immune microenvironments, inflammation, and imbalanced proteases/antiproteases.[48–50] Smokers who have COPD are at a three to six times higher risk of developing lung cancer compared to non-smokers with COPD, with a lung cancer incidence of 0.8 to 1.7%/year.[51] The occurrence of acute exacerbations in COPD patients increased the risk of lung cancer development by 2.77 times.[52] The majority of the patients affected with

lung cancer are common diagnosed at an advanced stage and Lung cancer appears frequently in patients with COPD.[53–55] Since patients with COPD undergo regular checkups in the hospital, it is reasonable to assume that lung cancer patients with COPD can hopefully be detected earlier in the clinical practice compared to patients without COPD. However, the overlapping symptoms of lung cancer and COPD may also lead to a delay in the diagnosis of lung cancer when patients with known COPD experience worsening symptoms of lung disease.[8,47,56] Lung cancer diagnosis and staging using an electronic nose (e-nose) based on machine learning is an emerging field in medical electronics with a diagnostic accuracy of 91.67%.[57,58] However, when applying the algorithm to other disease cohorts in a blinded fashion, the specificity of e-nose for LC diagnosis is low and its clinical applicability needs to be further validated.[59] Therefore, we need more accurate screening modalities to manage COPD combined with lung cancer and improve prognosis.

Chest CT scan can provide important information about pulmonary nodules, emphysema, and other fine structures, which is of great significance in the assessment of lung cancer risk in patients with COPD.[60] Patients with COPD are at a higher risk of developing lung cancer, especially in centrilobular emphysema,[61,62] and emphysema is also a risk factor for poor prognosis in lung cancer patients.[62–64] Quantitative CT (QCT) can analyze lung density, pulmonary vessel, and airway, and clearly shows the distribution of lung disease features such as emphysema, as shown in Figure 1. Mahajan et al[19] constructed a machine learning model based on the emphysema index, which has been shown to detect circulating tumor DNA mutations in COPD patients with lung cancer. AI is anticipated to utilize chest CT scans to categorize the risk level of isolated solid pulmonary nodules, facilitating early detection of lung cancer, as well as determine the pathological grade of the cancer, enabling a comprehensive and streamlined approach to managing lung cancer cases.[20–22] Recently, based on a large cohort study of 60,000 patients, C-Lung-RADS was proposed for Chinese patients, which assesses lung nodules in phases and multimodality, and provides doctors with a more professional and suitable solution for accurate diagnosis and assessment of lung nodules in the Chinese population.[23] In the future, it is expected that personalized CT evaluation systems for lung nodules will be developed for different populations in conjunction with the Lung-RADS.[65] Of interest, low-dose

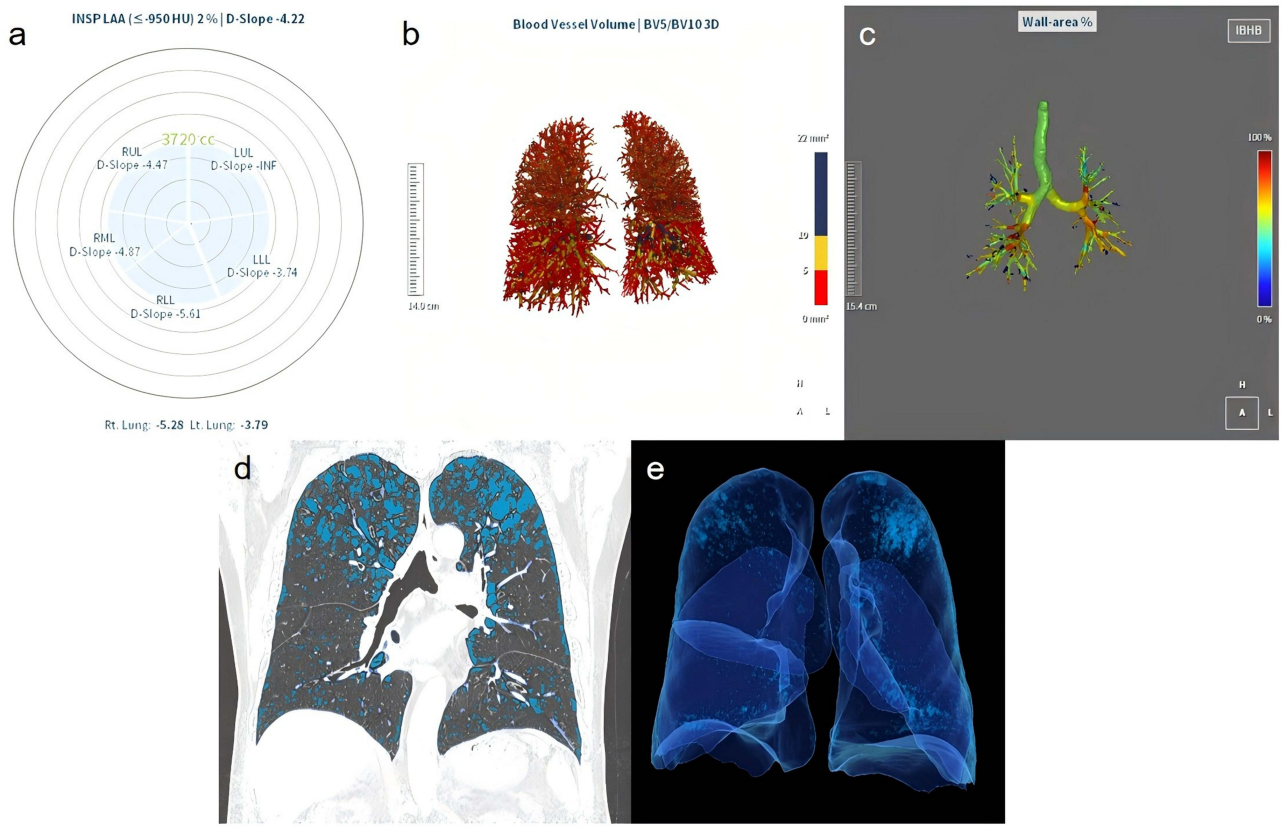

Figure 1 Quantitative CT analysis of lung density (**a**), airway (**b**) and vessel (**c**); (**d** and **e**): A 66-year-old male patient diagnosed with centrilobular emphysema.

computed tomography (LDCT), which reduces radiation dose and increases cost-effectiveness, has also been shown to be more effective in LCS.[66–68] At the same time, radiomics nomogram have been shown to predict COPD in lung cancer patients, enabling a one-stop shop for CT scans to check for both diseases in the broader context of LCS.[24,69,70] CT screening will go a long way toward reducing the risk of both lung cancer and COPD.

In addition, the treatment and prognosis for patients with lung cancer is also one of the hotspots of current research. CT radiomics model is able to assess lung cancer metastasis,[71] and the CT-based ensemble AI model can predict 10-year mortality and assess individualized structure risk scores.[25] Deep learning models are able to automatically draw approximate disease profiles for patients with primary lung lesions and/or hilar/mediastinal nodal disease.[72,73] Quantitative CT can assess immunotherapy response.[74] Relying on AI-assisted diagnosis technology, the personalized diagnosis and treatment system of lung cancer for different ethnic groups is expected to be popularized globally in the future, which will promote the early screening and early diagnosis of COPD patients with lung cancer, reduce the delay in the diagnosis of lung cancer that may be caused by the overlap of the symptoms of the two diseases, improve the early diagnosis rate and five-year survival rate of those who have a combination of lung cancer.

COPD and CVD

Compared to the general populace, individuals suffering from COPD are at an elevated risk of developing CVD, and associated with increased mortality.[75] Furthermore, acute exacerbations of COPD also increase the risk of CVD.[76,77] Existing guidelines underscore that individuals already predisposed to ischemic heart disease face an escalated threat of atherosclerotic cardiovascular disease complications subsequent to exacerbations of COPD.[8] However, there are no accepted guidelines for screening for comorbid CVD to mitigate this risk, which may lead to under-treatment of patients with comorbid CVD. Early recognition and management of comorbid CVD are of paramount importance. Early detection of CVD can be done by minimal checkup (eg, medical history, physical examination, blood tests, cardiovascular risk scoring) and, if further studies are needed, by imaging procedures such as chest CT.[78,79]

Multiple chest CT methods are associated with the incidence of CVD in COPD patients. Coronary calcification on chest CT imaging can predict coronary events occurring in the general population. The Agatston score is an imaging scoring method commonly used to assess the degree of coronary artery calcification, which is calculated based on multiplying the area of each calcified lesion by a weighting factor corresponding to the CT value of that calcified lesion.[80] The Weston score, a visual score that scores calcification in each major coronary vessel, correlates well with the quantitative Agatston score and can predict incident coronary artery disease (CAD) in patients with COPD.[26] This suggests that a routine chest CT can be used to assess CVD risk. Recent studies have found that coronary artery calcification (CAC) is a common additional finding on low-dose computed tomography for LCS. Calcification scoring on LDCT screening allows for simultaneous assessment of lung cancer and CVD risk. In the current era of LCS, this certainly provides research support for one-stop screening for both diseases.[81,82] Dual-energy CT (DECT) is capable of diagnosing coronary artery disease, whereas photon-counting CT (PCCT), which has fewer artifacts and higher signal-to-noise ratio, provides a 55% improvement in diagnostic confidence for coronary artery disease compared with DECT, and it shows that the diagnostic confidence for peripheral arterial disease may surpass that of DSA.[27,83] Coronary CT angiography (CCTA) plus fractional flow reserve (CT-FFR) is a method capable of mimicking coronary physiology to calculate the hemodynamic differences in the coronary microcirculation at maximal congestion. Study has shown that CT-FFR reduces the incidence of 90-day invasive coronary angiography, and has similar diagnostic accuracy to CCTA plus CT perfusion in detecting hemodynamically relevant CAD.[28,29] In our previous study, lung or mediastinal radiomics features based on CT can provide incremental predictive value over and above clinical risk factors in predicting CVD (AUC: 0.79, 95% CI [0.72, 0.86] for lung; 0.86, 95% CI [0.81, 0.92]) for mediastinum),[30,31] and two examples of applying dynamic nomogram are shown in Figure 2. AI in combination with CT undoubtedly provides significant assistance in screening for CVD.

For the management of CVD, the risk prediction of major adverse cardiovascular events (MACE) is undoubtedly crucial. There is an association between some imaging markers and MACE. In the clinical setting, the Agatston score is widely considered as the gold standard for calcification scores in cardiac CT scans and is significantly associated with MACE.[32] Physicians can stratify the risk of CVD based on the above imaging markers and further evaluate individuals at high risk.

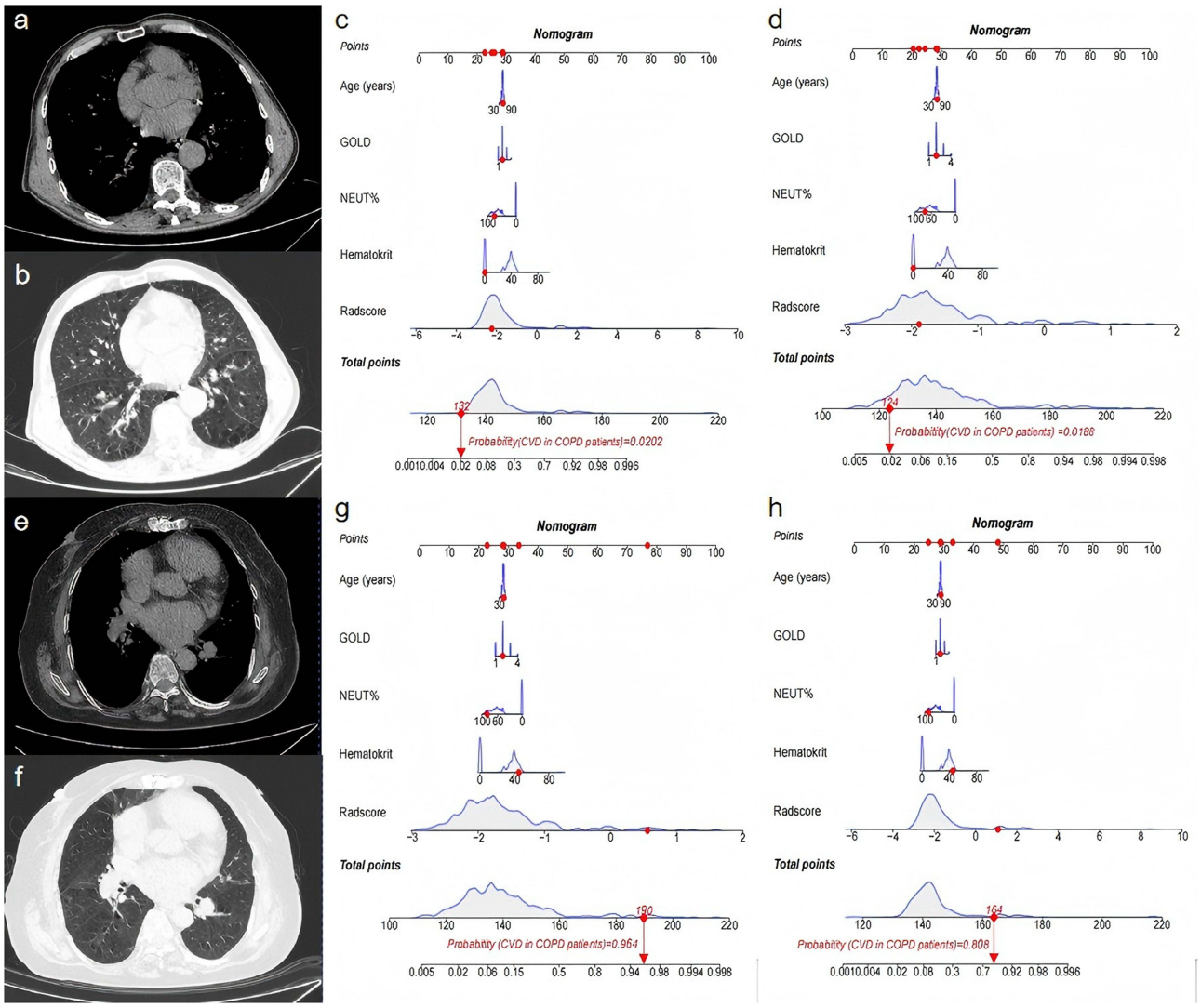

Figure 2 (**a**–**d**) A 73-year-old male patient diagnosed with COPD. The lung dynamic nomogram shows the total points were 132, and the corresponding prediction probability of CVD was 0.020; the mediastinum dynamic nomogram shows the total points were 124, and the corresponding prediction probability of CVD was 0.019. (**d**–**h**) A 73-year-old female patient diagnosed with COPD and coronary atherosclerotic heart disease. The dynamic nomogram shows the total points were 164, and the corresponding prediction probability of CVD was 0.808; the mediastinum dynamic nomogram shows the total points were 190, and the corresponding prediction probability of CVD was 0.964.
Abbreviations: COPD, chronic obstructive pulmonary disease; CVD, Cardiovascular disease.

Guidelines for the primary prevention of atherosclerotic cardiovascular disease (ASCVD) recommend a risk calculator (ASCVD risk score), with risk factors encompassing age, gender, smoking status, systolic blood pressure, hypertension treatment, total cholesterol level, high-density lipoprotein cholesterol level, and prevalent diabetes mellitus.[84] However, AI-guided quantitative coronary computed tomography angiography analysis has also been shown to have predictive value, with an AUC for 10-year MACE of 0.78.[33] With the help of AI, we can dig deeper into the information of imaging images, which is helpful to identify high-risk COPD patients for early cardiovascular risk adjustment.

COPD and Osteoporosis

Osteoporosis is an asymptomatic COPD comorbidity that is closely associated with COPD and often goes unrecognized clinically.[85] Osteoporosis is characterized by loss of bone mass and deterioration of the microstructure of bone tissue, leading to bone fragility and fractures.[86] A meta-analysis of 58 studies reported that the global prevalence of comorbid osteoporosis COPD was 38% and that COPD increased the likelihood of osteoporosis [odds ratio (OR) = 2.83].[87] Both acute exacerbation of COPD and recent fracture events are independent risk factors for progression in COPD patients with combined osteoporosis.[88,89] Fractures associated with COPD can further impair lung function and hinder daily

activities, creating a harmful cycle that puts a serious strain on these individuals; it contributes to poor health status and mortality.[85] Chronic inflammation of the airways and lungs in patients with COPD can stimulate bone resorption and impair bone formation, reduced physical activity due to dyspnea can lead to lower bone mass density (BMD), long-term use of corticosteroids in COPD patients can promote bone loss and increase the risk of osteoporosis, and there is also a common risk factor for both diseases, smoking.[90–92] However, the underlying mechanisms and physiological changes responsible for COPD-associated osteoporosis remain poorly understood and necessitate additional research.[91,93]

Dual-energy X-ray absorptiometry (DXA) is the gold standard for determining BMD.[94] However, DXA possesses inherent limitations, such as its planar technique, limited predictive sensitivity for fractures, and inadequate utilization in population-wide screening.[34,95] These deficiencies have restricted its universal adoption and impeded its practical implementation in clinical settings. The fracture risk assessment tool (FRAX) is a multivariate screening algorithm widely used in clinical practice to assess an individual's risk of fracture in osteoporotic patients over the next 10 years.[96] A CT-based fracture risk prediction model in the recent studies, capable of quantitatively separating and analyzing cortical and cancellous bone, provided a highly accurate and personalized prediction of fracture risk in COPD patients with a C-index of 0.797, and a prediction accuracy superior to that of the FRAX.[34,97] In contrast to the underutilization of DXA, CT scans are universally available for patients with COPD. Although CT scans are not commonly used to diagnose osteoporosis, they can improve overall screening for osteoporosis, and in combination with AI techniques have the potential to reduce the incidence of future fractures, especially in situations where DXA screening is often lacking. Studies have shown that the degree of emphysema on CT is a significant predictor of osteoporosis in patients with COPD, even after adjustment for competing risk factors (including age, sex, airflow obstruction, and corticosteroid use).[35–37] In QCT analyses, emphysema and vascular quantitative parameters were significantly associated with reduced BMD rather than airway parameters,[98] but it should be noted that the best predictors of osteoporosis risk events in patients with COPD still need to be further researched and validated as QCT parameters continue to be refined and deepened. However, the higher price and radiation dose of CT compared to DXA also poses a challenge to generalize its use in osteoporosis. At present, ultra-low dose hip CT-based automated method have been shown to be able to assess the bulk BMD of the proximal femoral subregion in COPD patients.[38] The automated method of fracture assessment based on LDCT is also highly accurate, further expanding the scope of LDCT.[39] Noticeably, LDCT, which reduces cumulative radiation exposure, will certainly be one of the most important research directions in the future.

COPD and Other Systemic Diseases

Sarcopenia, a progressive and generalized skeletal muscle disorder involving the accelerated loss of muscle mass and function, is a common comorbidity in patients with COPD, and its progression is linked to the severity of COPD; the prevalence of sarcopenia is relatively low in patients with stable COPD.[99–101] The estimated prevalence of sarcopenia among patients with COPD is 22%.[102] Significant transcriptional alterations were present in COPD patients with abnormal muscle fiber ratios.[99] Sarcopenia was associated with a higher risk of COPD mortality and impaired functional status.[40] CT is the preferred method for assessing muscle mass.[40] Dual-energy X-ray absorptiometry (DEXA) can be employed in research environments to quantify lean mass, bone mass, and fat mass; however, it is not routinely utilized for the assessment of muscle mass in clinical practice.[103,104] CT-derived cross-sectional area of the pectoralis major muscle (PMA) and attenuation of the pectoralis major muscle (PMT) are independent predictors of COPD severity.[41]

In addition to the quantification of muscle mass, excess adipose depots, ie, body mass index≥25, are associated with poor prognosis and outcome in COPD.[105,106] However, obesity is associated with lower mortality in patients with COPD, known as the obesity paradox.[107] Quantitative analysis of chest CT showed that a higher intermuscular adipose tissue index was linked to an elevated risk of mortality compared to a higher subcutaneous adipose tissue index among individuals with COPD.[40] High visceral adipose tissue area is also an independent risk factor for COPD exacerbation, and is associated with comorbidities (CVD) or risk factors (hypertension, hyperlipidemia, and diabetes) for COPD.[42,108] Previous study has shown that a deep learning model based on adipose tissue measured by quantitative CT can accurately predict COPD exacerbations.[42] Nevertheless, the existence of the obesity paradox suggests that "normal" versus "abnormal" adipose tissue and its distribution need to be studied in greater depth, and a more comprehensive

understanding of how these metrics can be used to risk-stratify patients with COPD is needed in order to improve the long-term prognosis of COPD patients more effectively.

Pulmonary hypertension (PH) is a complication of COPD, which plays an important role in its progression to cardiopulmonary disease.[109] The progression of PH is linked to clinical decline, deterioration in gas exchange, and heightened mortality rates among individuals with COPD.[110] Patients suffering from both COPD and PH (COPD-PH) exhibit greater functional impairment and a poorer prognosis compared to those with idiopathic pulmonary arterial hypertension (PAH).[109] Although right heart catheterization is the gold standard for the diagnosis of pulmonary hypertension, its invasive nature limits its use as a screening tool in many populations, particularly in those without clinically significant symptoms.[105] Before considering referral for invasive right heart catheterization, it is beneficial to use noninvasive methods to identify individuals at risk for PH for initial screening. On chest CT images, the diameters of the pulmonary artery and the ascending aorta (PA/A) ratio of 1 or greater are both reliable indicators of pulmonary hypertension and associated with an increased risk of acute exacerbations and long-term mortality in patients with COPD.[43,44,111] AI cardiac CT segmentation is an efficient and accurate method, and these segmenting are in good agreement with the radiologist's segmentation, thereby providing clinically valuable indicators in a shorter time. Moreover, AI-based lung parenchyma assessment can accurately identify and quantify lung disease patterns by integrating multiple radiomics techniques, such as texture analysis and classification, providing important indicators for the diagnosis, phenotype, and prognosis of patients with PH.[112] These studies suggest that noninvasive markers on chest CT scans may increase the frequency of PH detection in a susceptible COPD population.

The Challenge of AI Adoption

The performance of AI is highly dependent on the quality, diversity and representativeness of the training data. If the data is biased, the model may output biased results and risk misdiagnosis. And when there is insufficient data, the model is prone to overfitting or underfitting.[113] Deep learning models are often regarded as "black box" and lack of interpretability, which also limits the debugging and optimization efficiency of the models. In the actual implementation process, AI may face data silos, format inconsistency and other issues, and need to invest in high-cost cleaning and labeling data. There are also high requirements for computing power. Further, regular training for physicians is needed to better apply and debug AI models.[113,114] Further, AI models require certain development and maintenance costs, and AI systems need to continuously update data and algorithms. However, in terms of long-term benefits, AI models are expected to reduce labor costs and increase diagnostic accuracy.[18,113] In future research, small-scale pilot applications of AI models in clinical practice are also needed to assess the predictive performance and clinical utility of the models. The performance of the model should also be monitored in real time during the application process to ensure that its performance on new data is consistent with the training data, and then the model can be optimized.

Conclusions

In response to the current absence of standardized guidelines for managing COPD comorbidities, this review innovatively synthesizes cutting-edge studies on AI combined with CT. This is expected to lead to one-stop screening of COPD comorbidities using CT scans in the future. AI tools have are capable of recognizing high-risk features in all structures visible on the CT scan, and have led to research advances in the assessment, diagnosis, prognosis, and prediction of the disease. The development of chest CT technology requires parallel development of AI techniques to maximize the use of more detailed pathophysiological data. Integration of these tools into clinical practice could provide real-time support to improve diagnostic accuracy and facilitate early detection of COPD comorbidities unrelated to the primary indication for scanning, followed by early intervention and risk adjustment, perhaps yielding meaningful improvements in prognosis and quality of life for COPD patients. However, due to the inherent limitations of AI models, there is still a long way to go for future clinical applications. Collaborative and focused research endeavors in this field will ultimately lead to deeper comprehension and more effective management of COPD worldwide.

Abbreviations

AI, Artificial Intelligence; ASCVD, atherosclerotic cardiovascular disease; BMD, bone mass density; CAC, coronary artery calcification; CAD, coronary artery disease; CCTA, Coronary CT angiography; COPD, Chronic obstructive

pulmonary disease; CT-FFR, fractional flow reserve; CVD, cardiovascular disease; DECT, Dual-energy CT; DXA, Dual-energy X-ray absorptiometry; DEXA, Dual-energy X-ray absorptiometry; FRAX, fracture risk assessment tool; LCS, lung cancer screening; LDCT, low-dose computed tomography; MACE, major adverse cardiovascular events; PA/A, the diameters of the pulmonary artery and the ascending aorta; PAH, pulmonary arterial hypertension; PCCT, photon-counting CT; PFT, pulmonary function test; PH, Pulmonary hypertension; PMA, pectoralis major muscle; PMT, pectoralis major muscle; QCT, quantitative CT; SPECT, Single-Photon Emission Computed Tomography.

Disclosure

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