JOURNAL OF INTERNATIONAL CRISIS AND RISK COMMUNICATION RESEARCH
ISSN: 2576-0017
2024, VOL 7, NO S8

# The Role of Radiology in Bronchiectasis Evaluation: Insights from CT, MRI, and Emerging Technologies

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**Abstract**

Bronchiectasis is a chronic lung condition characterized by abnormal dilatation and lack of tapering of the airways. Computed tomography (CT) and magnetic resonance imaging (MRI) have significantly advanced the detection and evaluation of bronchiectasis. CT imaging plays a central role in identifying key features of bronchiectasis, such as airway dilatation, lack of tapering, and the presence of mucus plugging. Visual CT scoring systems, while effective, are limited in their ability to comprehensively assess both the extent and severity of bronchiectasis. Computer-based image analysis, including deep learning techniques, shows promise in enhancing diagnostic precision, tracking disease progression, and predicting clinical outcomes. However, the development of reliable algorithms requires large and diverse datasets to ensure unbiased training data. Collaborative networks are expected to be valuable resources in developing bronchiectasis-specific computer algorithms. The primary value of computer analysis lies in tracking disease severity and changes over time, with a focus on measuring longitudinal disease progression. MRI, particularly with hyperpolarized noble gases, offers a sensitive alternative for detecting ventilatory defects, making it valuable for longitudinal monitoring of disease, especially in pediatric cases. The combination of quantitative CT analysis, improved MRI techniques, and computational tools holds great promise for revolutionizing the assessment of bronchiectasis, improving prognostic accuracy, and providing valuable insights for personalized treatment plans in the future.

**Keywords:** Bronchiectasis, Radiology, High-Resolution Computed Tomography (HRCT), Magnetic Resonance Imaging (MRI), CT Imaging, MRI in Bronchiectasis.

## Introduction

Within the lungs, airways and pulmonary arteries run adjacent to each other within the peribronchovascular interstitium, a connective tissue structure that is located centrally in the secondary pulmonary lobule. On computed tomography (CT) imaging, bronchi and pulmonary arteries divide at regular

intervals within the lung lobes. The bronchi bifurcate or trifurcate, with the parent airway dilating prior to separating into its daughter branches. Each division of an airway gives rise to a new airway generation, and the length of the airway between these divisions is referred to as an airway segment. Under normal physiological conditions, airways gradually taper, with their cross-sectional area narrowing as they approach the lung periphery. Bronchiectasis reflects the consequences of airway damage and is typically characterized by abnormal airway dilatation and a lack of tapering. It is associated with various pulmonary conditions, and visual scoring systems applied to CT imaging have been employed, either independently or in conjunction with clinical parameters and pulmonary function tests, to evaluate a patient's disease burden. Advances in computer-based analysis have the potential to enhance the precision and sensitivity in detecting disease burden and tracking its progression on CT imaging. Consequently, such tools may play a significant role in assessing treatment responses in clinical trials and monitoring disease behavior in real-world scenarios. This review will discuss the imaging characteristics of bronchiectasis on CT and magnetic resonance imaging (MRI), the utility of semi-quantitative visual CT scores for disease characterization, and recent research deploying objective computer-based quantitative image analysis in patients with bronchiectasis. Additionally, we will explore the potential advantages and challenges associated with these tools in the future.

**Defining Bronchiectasis on Computed Tomography**

Bronchiectasis was initially described in the early 19th century by René Laennec in patients with tuberculosis. This diagnosis was based on careful auscultation of the lungs and confirmed by correlating clinical findings with postmortem observations. Today, volumetric CT imaging has facilitated the identification of abnormal airways in the lungs. However, the definition of bronchiectasis on CT remains a topic of debate. For the purposes of this review, only free-standing bronchiectasis, which represents airway dilatation against a backdrop of low attenuation lung, will be considered. Traction bronchiectasis, which results from lung interstitial fibrosis pulling open peripheral airways, will not be addressed.

Pathologically, bronchiectasis is defined as "irreversible localized or diffuse bronchial dilatation, usually resulting from chronic infection, proximal airway obstruction, or congenital bronchial abnormality" (Hansell et al., 2008). On CT imaging, three features are typically used to define bronchiectasis:

1. A pulmonary arterial diameter that is larger than the luminal diameter of the corresponding airway.
2. A lack of tapering of airways as they extend toward the lung periphery.
3. The presence of visible airways within the most peripheral 1 cm of the lung.

**Bronchial Luminal Diameter Larger Than Pulmonary Artery**

The assessment of bronchus size relative to the corresponding pulmonary artery has historically been a critical metric for identifying bronchiectasis (Hansell et al., 2008). However, over time, it has become evident that this method has the potential to overestimate or underestimate the presence of bronchiectasis. Physiological variations, such as those observed in individuals living at high altitudes and normal aging processes can result in non-pathological airway dilatation. Misleading interpretations of bronchiectasis may also occur on CT imaging when an artery divides before its corresponding airway, leading to a comparison with an airway of an earlier generation. This phenomenon is particularly common in the airways of the right middle lobe and lingula.

Pathological conditions, such as smoking-related lung injury or hypoxic vasoconstriction (Dunham-Snary et al., 2017) in regions of chronic lung disease, can cause pulmonary arteries to narrow, creating a false impression of airway dilatation (Diaz et al., 2017). Conversely, when airways are genuinely dilated, suboptimal inspiratory effort during CT image acquisition may lead to underestimation of bronchiectasis, as airways are not fully inflated. Given these limitations, reliance on airway enlargement relative to adjacent arteries is no longer sufficient as a sole criterion for diagnosing bronchiectasis on CT imaging.

**Airways Within 1 cm of the Pleural Surface**

In healthy individuals, the walls of peripheral airways are thinner than the resolution limits of CT imaging. Consequently, small airways with luminal diameters of less than 2 mm are usually imperceptible on imaging, as the air within the airway lumen merges with the surrounding air. However, bronchiectatic small airways exhibit thickened walls and widened lumens, making them visible in the lung periphery.

Requiring airway dilatation to be visible in the lung periphery for diagnosing bronchiectasis presents challenges in diseases characterized by central rather than peripheral bronchiectasis.

**A Lack of Airway Tapering**

The most specific feature of bronchiectasis identified on CT imaging is the "lack of tapering of bronchi" as the airways progress from the central regions of the lung towards the periphery. Detecting a lack of tapering requires meticulous examination of the CT images, ideally by an expert. This feature is typically evaluated along the entire length of an airway, from the lobar bronchi to the distal airways. Additionally, comparing adjacent airway segments can provide a more localized assessment of whether the airways are tapering appropriately.

CT imaging often reveals accessory signs associated with bronchiectasis, such as bronchial wall thickening and mucus accumulation within dilated airways. In larger airways, mucus or debris may obstruct the lumen, appearing on CT as mucus plugging. Tracing a plugged airway proximally toward the lung's center can

help distinguish a blocked airway from a pulmonary vessel, a frequent source of misinterpretation. In smaller airways, debris or mucus occluding the lumen, referred to as an exudative bronchiolitis pattern, manifests as tree-in-bud nodularity. This pattern represents a branching appearance of solid tubes indicative of non-hollow airways.

An indirect indicator of small airway disease on CT imaging is a mosaic attenuation pattern, where areas of reduced attenuation on inspiratory CT reflect air trapping within the acini of the secondary pulmonary lobule (Ridge et al., 2011). Expiratory CT, routinely performed today, accentuates the density differences between air-trapped regions resulting from small airways disease and normal lung tissue, which increases in density as air exits the alveoli during expiration. It is noteworthy that when airway walls are thickened, comparing the inner airway wall diameter to the pulmonary artery may underestimate the overall burden of bronchiectasis (Kuo et al., 2017).

Identifying at least two of the three primary imaging features of bronchiectasis, alongside accessory findings such as bronchial wall thickening, mucus plugging, tree-in-bud nodularity, and evidence of small airways disease, enhances diagnostic confidence.

**Classical Descriptive Appearances**

Bronchiectasis is traditionally classified into three patterns on CT imaging. Cylindrical bronchiectasis, the most common form, presents as smooth airway dilatation throughout its length. Varicose bronchiectasis appears as a ruffled, beaded airway contour and is often associated with allergic bronchopulmonary aspergillosis (ABPA) or post-tuberculous airway damage. Cystic bronchiectasis, where airways are dilated into rounded, spherical shapes, is typically linked to cystic fibrosis or prior tuberculosis infections.

The distribution of bronchiectasis within the lung can also offer clues about the underlying etiology. Central bronchiectasis is frequently observed in ABPA, cystic fibrosis, and congenital tracheobronchomegaly (Mounier-Kuhn syndrome). Peripheral bronchiectasis, on the other hand, may exhibit a lobar distribution that provides further insights into the disease's origins.

**Clinical CT Evaluation**

The optimal method for evaluating bronchiectasis on CT involves a volumetric scan with axial slices no thicker than 1 mm. Reconstructions in sagittal and coronal planes can further aid in identifying airway dilatation and lack of tapering. In longitudinal studies, it is critical to use the same CT scanner and reconstruction settings at each time point to minimize scanner-related variability.

While extensive research has been conducted on the measurement variability of pulmonary function tests, the variability associated with CT-based measurements is less well understood. Accurately distinguishing between genuine disease progression and changes caused by measurement variation is essential for developing reliable prognostic tools. Additionally, variability in patient effort between CT scans can significantly impact the assessment of bronchiectasis severity.

Follow-up CT scans for bronchiectasis are typically performed when clinical deterioration occurs, often accompanied by symptoms such as breathlessness, rather than at regular intervals. A CT scan performed during an exacerbation may provide valuable information, such as the presence of infection, but is likely to be of inferior quality compared to scans acquired when the patient is clinically stable. Consequently, such scans are limited in their ability to depict the natural history or trajectory of the disease.

**Visual Scoring of Bronchiectasis**

Several visual scoring systems have been developed to evaluate bronchiectasis-related lung damage on CT. These scoring methods typically use categorical scales to assess various imaging features on a lobar basis. However, a key limitation of these semi-quantitative systems is the way they address bronchiectasis extent and severity as competing variables in prognostic models. Separating the effects of disease extent from those of disease severity oversimplifies the condition. For instance, subtle airway dilatation in three bronchopulmonary segments (extensive disease) is not easily compared to marked airway dilatation in a single segment (severe disease). Current visual scoring systems lack a straightforward, reproducible method to simultaneously account for both extent and severity, an area where computational analyses could provide significant improvements.

Detailed visual scoring systems, such as the Brody (Goeminne et al., 2012) and Bhalla (Diab-Cáceres et al., 2021) scores, are frequently used by specialists. However, these lobar-based scoring methods are time-consuming and may show variable inter-observer agreement (de Brito et al., 2017), limiting their real-world clinical applicability. Nevertheless, such scores can identify unique imaging phenotypes of bronchiectasis (Cowman et al., 2018).

Assessing disease progression using longitudinal CT imaging poses additional challenges with visual scoring methods. Some regions of the lung may appear improved (e.g., reduced mucus plugging), while others show disease worsening, leading to an incomplete picture of disease progression. Current visual scoring techniques typically analyze changes at a whole-lung level, which may obscure localized variations in disease

extent or severity. Developing robust approaches to track bronchiectasis-related progression on CT remains a critical unmet need.

**Multidimensional Scoring Systems**

Multidimensional bronchiectasis scoring systems integrate clinical, imaging, and functional data to estimate overall disease burden. These systems are generally less complex than detailed visual scores, as they rely on a limited number of imaging variables. Examples include the use of bronchiectasis extent in the FACED score (which incorporates forced expiratory volume in 1 second, age, chronic colonization, extension, and dyspnea) (Martinez-Garcia et al., 2017), and the Bronchiectasis Severity Index, which considers bronchiectasis extent and the presence of cystic bronchiectasis (McDonnell et al., 2016).

The Bronchiectasis Radiologically Indexed CT Score (BRICS) incorporates bronchiectasis severity and the number of bronchopulmonary segments affected by emphysema. These simplified systems demonstrate promise for clinical application, particularly in cases where detailed imaging phenotyping is not feasible.

**Computer Analysis of Bronchiectasis**

Over the last decade, significant advancements in computer processing power have facilitated the emergence of quantitative medical image analysis. This field aims to utilize computational methods to identify and measure structures within organs such as the lung at the voxel level. By quantifying the number of voxels and analyzing the spatial distribution of structures within the lung, it becomes feasible to provide objective measurements that distinguish healthy from diseased tissue. The earliest approaches used Hounsfield unit (HU) density thresholds to classify tissue types, such as emphysema.

In the context of bronchiectasis, a major challenge is the computational delineation and measurement of airways within the lung. In theory, identifying all the voxels constituting the airways on a CT scan could enable the calculation of detailed airway volume. Expressing this airway volume as a percentage of total lung volume would normalize the measurement for individual differences, such as patient size and gender. Furthermore, measuring the inner and outer airway wall diameters could yield estimates of airway wall thickening.

However, computational airway analysis involves two complex processes. The first is airway lumen identification, termed segmentation. The second stage involves specific calculations to characterize or quantify airway features indicative of damage, all of which depend on accurate segmentation. Several factors influence the ability to segment airways on CT scans (DeBoer et al., 2014). These include inherent quantum noise, which results in image graininess and is affected by factors such as radiation dose, detector size, and patient size. Quantum noise is more pronounced in low-dose CT scans. The reconstruction algorithm used for CT acquisition also significantly impacts the image's interpretability by computational systems.

Axial slice thickness, ideally <1.5 mm, influences spatial resolution, and modern iterative reconstruction algorithms designed to reduce radiation exposure denoise the image but can appear different to computational systems compared to traditional filtered back projection techniques. High-resolution algorithms enhance visual contrast or employ edge enhancement of linear structures, which benefits manual interpretation but can hinder computational analysis. Standardized, computer-compatible reconstruction kernels have been proposed to facilitate consistent computational interpretation and enable robust comparisons across timepoints. However, proprietary algorithms used by commercial scanner manufacturers have limited this standardization.

Other challenges common to both computer and visual CT analyses include artifacts caused by breathing, infection obscuring visible airways, suboptimal inspiration during scans, and inconsistent CT acquisition protocols between timepoints.

**Quantitative CT Analysis**

Quantitative CT (QCT) metrics generally follow one of three analytic approaches:

1. **Real physical properties**: Metrics such as airway diameter, often used in visual CT scoring.
2. **Texture analysis**: Classification of small regions or patches of the CT scan based on their appearance, using radiological terminology to describe patterns.
3. **Latent features**: Characteristics identified by computational methods that may not have direct visual equivalents.

**Number of Resolvable Airways**

As bronchiectasis progresses, more airway segments become visible on CT scans. Quantifying these segments through computational tools offers a potentially powerful indicator of disease extent. This can be accomplished by calculating the number of airway segments between branching points using volumetric imaging and segmentation techniques (Santos et al., 2016). However, such methods are heavily dependent on the CT acquisition protocol and reconstruction kernels employed.

**Airway Measurements**

Airway measurements typically involve either airway diameters or cross-sectional areas, measured in a plane perpendicular to the airway's central axis (Quan et al., 2018). Visual comparisons of the inner airway wall diameter with the pulmonary artery are commonly used to detect bronchiectasis, but airway wall inflammation can make lumen size appear smaller than it is, masking the presence of bronchiectasis. Consequently,

computational analyses often rely on measurements of the outer airway wall for determining airway diameter and cross-sectional area.

Studies in cystic fibrosis (CF) and smokers with radiological bronchiectasis indicate that airway lumen size does not significantly differ from control populations. However, measurements involving the outer airway wall show significant differences in both airway size and wall thickness between disease populations and healthy controls (Wielpütz et al., 2013).

**Airway Tapering**

Computational analysis can assess airway tapering by measuring cross-sectional areas or diameters at regular intervals along the airway centerline (Quan et al., 2018). However, transient dilatation at airway bifurcations may create artifacts resembling bronchiectasis. A study focusing on tapering metrics found reduced airway tapering in pediatric CF patients compared to healthy participants, using both inner and outer airway wall measurements (Kuo et al., 2020). While tapering metrics are effective for cylindrical bronchiectasis, assessing tapering in varicose and cystic bronchiectasis, where dilatation and narrowing coexist, poses challenges.

**Air-Trapping**

Airway inflammation, narrowing, and loss of compliance can lead to air trapping within the acinus. While blocked airways may not be visible on CT, their consequences, such as dilated secondary pulmonary lobules, are detectable on inspiratory scans and accentuated on expiratory CT scans. Air-trapping can be quantified at the voxel level using simple methods that apply HU density thresholds (e.g., -850 HU) on expiratory CT scans (Robinson et al., 2020).

The parametric response map method compares HU density changes across registered inspiratory and expiratory scans to classify emphysema and functional small airway disease. On inspiratory CT, voxels with an HU density <-950 are categorized as emphysema, while on expiratory CT, non-emphysematous voxels with a density <-856 represent functional small airway disease. Varying HU thresholds have been used to assess air-trapping severity. Techniques like real-time spirometric feedback during CT acquisition can optimize inspiratory and expiratory breath holds.

**Airway-Artery Ratio**

Visual assessment challenges with the airway-artery ratio in detecting bronchiectasis have been previously noted. Quantitative measurements of this ratio have shown significant correlations with CF disease severity in adolescents. Among adult smokers with radiological bronchiectasis, a higher airway-artery ratio was observed compared to controls, attributed to smaller arteries in patients rather than larger airways.

**Other QCT Measures**

Additional quantification methods, although less frequently reported, include vessel volume analysis. Peripheral vascular pruning, indicated by a reduction in the volume of small vessels (<5 $mm^2$), has been observed in smokers with mild bronchiectasis and is associated with reduced six-minute walk distances and forced expiratory volume in 1 second (Diaz et al., 2018).

Automated CT density analyses have grouped different HU values within the lung into distinct thresholds, either fixed or adaptive based on whole-lung HU histograms. Studies in adults with CF found that density thresholds correlated better with disease severity over time than visual CT scores (Chassagnon et al., 2018). Similarly, adaptive thresholds in patients with primary ciliary dyskinesia correlated with baseline severity measures, such as forced expiratory volume in 1 second (FEV1) and forced vital capacity (FVC), more effectively than visual CT scoring (Hoang-Thi et al., 2018).

A study by Xing et al. (2020) analyzed 103 computer-derived CT variables representing latent CT features (Xing et al., 2020). The study demonstrated that features indicative of bronchiectasis effectively differentiated non-tuberculous mycobacterial infections from pulmonary tuberculosis.

**Challenges in Bronchiectasis Quantification**

A significant proportion of quantitative studies reviewed have been conducted in cystic fibrosis (CF) patients. The abundance of imaging data in CF facilitates its study and the development of automated tools. However, transferring computer-based tools developed for CF populations to non-CF bronchiectasis populations will require fine-tuning and optimization to account for the unique imaging characteristics of these diseases. Optimizing computer algorithms necessitates large datasets encompassing diverse imaging parameters and patient characteristics to ensure unbiased training data.

The effectiveness of computer algorithms is strongly dependent on the quality and diversity of the training datasets used during development. If the datasets do not adequately represent variations in age, gender, ethnicity, socioeconomic background, or geographic distribution, there is a substantial risk of introducing biases into the model. To create algorithms that perform reliably and generalize well to new datasets, training must involve large and diverse datasets. Collaborative networks such as Bronch-UK and EMBARC are expected to serve as valuable resources in developing bronchiectasis-specific computer algorithms.

Emerging deep learning techniques present additional challenges. For instance, while an algorithm may predict poor clinical outcomes for a patient, it may not be able to visually demonstrate the specific CT features that underpin this prognosis. The ability to visualize the basis of a computer's predictions is critical to gaining the trust of both clinicians and patients, ensuring confidence that the model's decisions are appropriate. Understanding computer-derived imaging features also facilitates the biological interpretation of these features, helping to explain their connection to reduced survival. Such insights could contribute to clarifying disease pathophysiology and guiding drug development.

Although visual CT evaluation remains adequate for detecting disease, the primary value of computer analysis lies in tracking disease severity and changes over time. Consequently, the focus of quantitative CT metric development is likely to shift toward measuring longitudinal disease progression, a task beyond the precision of human observers. Achieving this goal will require extensive and diverse longitudinal datasets for training. Future algorithms will need to emphasize enhanced automated airway segmentations to identify abnormal peripheral airways effectively and detect and quantify mucus plugging—an area where deep learning approaches may prove particularly effective (Nardelli et al., 2018).

**Quantitative MRI Analysis**

Compared to MRI, CT imaging offers a higher signal-to-noise ratio and faster acquisition times, enabling an entire study to be completed within a single breath hold, minimizing motion artifacts. CT's superior spatial resolution also allows for the visualization of a greater number of smaller airway branches. However, the primary limitation of CT imaging is patient exposure to ionizing radiation, which raises long-term cancer risks, particularly for young patients undergoing repeated scans, such as those with cystic fibrosis or primary ciliary dyskinesia.

To mitigate these risks, MRI is increasingly used in younger populations with airway diseases. MRI offers additional advantages, including insights into the functional effects of lung disease. Quantitative MRI studies often focus on detecting ventilatory defects. Differences in non-contrast-enhanced MR signal intensity between inspiratory and expiratory scans have been shown to correlate with lung function metrics in CF patients (Pennati et al., 2020).

The use of inert hyperpolarized noble gases, such as ^3He, during MRI acquisition enhances the magnetization of the gas's MR spin, significantly improving the signal-to-noise ratio in lung imaging. When hyperpolarized gas diffuses into the airspaces, lung ventilation can be quantified by assessing areas with low ^3He MR signals. In bronchiectasis patients, ventilatory defects quantified through this method have been shown to be greater in lung lobes with visible bronchiectasis on CT and even in lobes without bronchiectasis compared to healthy individuals (Marshall et al., 2017). Additionally, airway clearance therapy has been demonstrated to improve ventilatory defects in non-CF bronchiectasis patients (Svenningsen et al., 2017).

The detection of ventilatory defects using hyperpolarized gas MRI is likely to provide a sensitive method for identifying early lung damage, particularly in younger populations, while avoiding the risks associated with radiation exposure (Marshall et al., 2017).

**Conclusion**

In conclusion, the detection and evaluation of bronchiectasis have significantly advanced with the advent of modern imaging technologies, particularly through computed tomography (CT) and magnetic resonance imaging (MRI). These imaging modalities provide detailed insights into the structure and pathology of the lungs, with CT playing a central role in detecting and quantifying bronchial changes such as airway dilatation, loss of tapering, and the presence of mucus plugging. Despite the effectiveness of visual CT scoring systems, they remain limited in their ability to assess both the extent and severity of bronchiectasis comprehensively. As such, computer-based image analysis, including deep learning techniques, is proving to be a promising tool for enhancing diagnostic precision, tracking disease progression, and predicting clinical outcomes.

Furthermore, while CT remains the gold standard for bronchiectasis evaluation, its limitations—such as radiation exposure—are being mitigated by the use of MRI, especially in younger populations. The emerging use of hyperpolarized noble gas MRI offers a sensitive alternative for detecting ventilatory defects, making it a valuable non-invasive option for longitudinal monitoring of disease, particularly in pediatric cases. The combination of quantitative CT analysis, improved MRI techniques, and computational tools holds great promise for revolutionizing the assessment of bronchiectasis, improving prognostic accuracy, and providing valuable insights for personalized treatment plans in the future.

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