ORIGINAL RESEARCH

# Bibliometric Analysis of Pulmonary Fibrosis Imaging Research: Knowledge Graph Construction Based on the Web of Science Core Database

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## Abstract

**Aim**

To quantify publication trends, map international collaboration networks, and identify dominant and emerging research themes in Pulmonary fibrosis(PF) imaging (2015–2024).

**Methods**

A structured Web of Science search combining PF- and imaging-related terms yielded 1,159 English-language original research articles. Analyses employed CiteSpace, VOSviewer, and Scimago Graphica for trend assessment, keyword co-occurrence, citation burst detection, and collaboration network visualization.

**Results**

Annual publication volume showed sustained linear growth ($R^2 = 0.867$). Researchers from 64 countries contributed; the United States led in output (332 publications) and citation impact (9,821 citations), while China ranked second in volume (224 publications) with lower proportional citation impact. The Western Europe–North America axis showed the densest collaborative ties. Keyword co-occurrence revealed close thematic links among idiopathic pulmonary fibrosis, high-resolution computed tomography (HRCT), usual interstitial pneumonia (UIP), survival, and mortality. Citation burst analysis identified "deep learning" as the strongest and most sustained burst (2021–2024), by which point it had shifted from exploratory method to established domain. Three overlapping research phases emerged: diagnostic framework consolidation (2015–2018), computational computed tomography (CT)-based phenotyping (2016–2022), and therapeutic expansion toward antifibrotics and progressive fibrosing interstitial lung disease (2019–2024).

**Conclusion**

PF imaging research has shifted from diagnostic consensus toward quantitative CT biomarkers and artificial intelligence(AI)-driven phenotyping, driven by the need to reduce interobserver variability and enable individualized risk stratification. Geographic fragmentation and limited multicenter validation remain key barriers to AI generalizability. Future priorities include standardized imaging protocols, prospective multicenter validation cohorts, and integration of AI-driven CT phenotyping with multi-omics and circulating biomarkers for prognostic precision.

**Keywords:** pulmonary fibrosis; bibliometric analysis; HRCT; deep learning; CT quantitative imaging.

## Introduction

Pulmonary fibrosis (PF) encompasses a heterogeneous group of interstitial lung diseases defined by progressive parenchymal fibrosis[1], deteriorating lung function, and poor prognosis[2]. Idiopathic pulmonary fibrosis (IPF), the most prevalent and clinically aggressive form, carries a median survival of 2–3 years from diagnosis despite recent advances in antifibrotic therapy[3]. High-resolution computed tomography (HRCT) has become the primary imaging modality for PF diagnosis and staging, capable of identifying characteristic fibrotic patterns and, in appropriate clinical contexts, obviating the need for surgical lung biopsy[4,5]. Nevertheless, HRCT assessment is burdened by inherent practical constraints: subjective visual interpretation produces substantial interobserver variability, particularly when discriminating typical usual interstitial pneumonia (UIP) from probable UIP, indeterminate for-UIP, or alternative diagnoses—a distinction with direct consequences for diagnostic certainty, prognostic accuracy, and treatment eligibility[6].

The diagnostic and management framework for PF has evolved substantially over the past decade. The 2018 American Thoracic Society / European Respiratory Society / Japanese Respiratory Society / Latin American Thoracic Association (ATS/ERS/JRS/ALAT) guideline formalized HRCT pattern-based classification into four categories (UIP, probable UIP, indeterminate for UIP, and alternative diagnosis), elevating imaging from a supportive to a central diagnostic role[7]. The 2022 guideline update extended this framework to progressive pulmonary fibrosis (PPF) and reframed the core clinical question from "Are imaging features consistent with IPF?" to "What is the patient's risk of progressive fibrosis, and when should treatment be initiated?"[8,9]. This reorientation acknowledges that diagnostic accuracy alone is insufficient: clinicians additionally require early identification of patients at high risk of rapid progression, precise phenotyping to guide targeted therapy selection, and individualized prediction of disease

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trajectories and treatment response. Standard visual HRCT interpretation inadequately addresses these prognostication-centric demands because of inherent subjectivity and inconsistent reproducibility across readers and institutions[10].

Quantitative imaging methods and artificial intelligence (AI) offer potential solutions to these limitations. Automated computed tomography (CT) analysis—encompassing computational measurement of reticulation extent, honeycombing distribution, and traction bronchiectasis—has demonstrated superior prognostic discrimination over conventional clinical severity indices[11,12]. Deep learning and machine learning enable large-scale automated segmentation and radiomics feature extraction; growing evidence supports their ability to predict IPF progression rates and mortality independently of clinical variables[13-15]. Whether these methods adequately address real-world diagnostic and prognostic demands, however, remains to be established. Key barriers to clinical translation persist: limited interpretability, training-data bias, absent multicenter validation, and unstandardized reporting workflows.

Bibliometric analysis offers a systematic, quantitative means of characterizing research trajectories, identifying emergent methodological paradigms, and assessing alignment between research investment and clinical priorities16. Examination of publication volume trends, keyword co-occurrence, citation dynamics, and collaboration networks enables assessment of which research questions receive sustained scientific attention, which methodological innovations achieve lasting traction versus transient prominence, and how geographically distributed research communities orient their efforts around shared clinical goals. Such methods have proved valuable across diverse medical specialties; they have not, however, been rigorously applied to PF imaging research, limiting understanding of how existing research investments correspond to unmet clinical needs in diagnostic precision, prognostication, and therapeutic monitoring.

This bibliometric analysis examines the global PF imaging literature from 2015–2024 to characterize publication trends, identify dominant research themes and emergent methodological concentrations, evaluate international collaboration patterns, and synthesize findings to inform future research priorities. In this study we used the Web of Science (WOS) database, whose advantages include broad coverage of high-quality, multidisciplinary journals, standardized indexing and citation data for reproducible bibliometric analysis, and robust search and citation-tracking features that enhance the comprehensiveness and comparability of the literature retrieval. Situating these quantitative findings within their clinical context, we aim to determine which research directions have achieved sustained momentum, identify gaps between research emphasis and clinical implementation needs, and offer a data-driven assessment of the field's trajectory toward precision diagnosis, risk stratification, and individualized management across PF and related fibrotic lung diseases.

## Methods

The bibliometric analysis in this study follows three sequential steps. The detailed retrieval and screening process is illustrated in Figure 1.

### *Data Sources*

This study utilized the core database of Web of Science (hereinafter referred to as WOS), selecting the two sub-databases: Science Citation Index Expanded (SCI-E) and Social Sciences Citation Index (SSCI). A professional retrieval expression was constructed as follows: (TS=("pulmonary fibrosis") OR TS=("pulmonary fibroses") OR TS=("fibrosing alveolitis") OR TS=("lung fibrosis") OR TS=("lung fibroses") OR TS=("fibrosing alveolitides") OR TS=("fibrotic lung disease") OR TS=("fibrotic lung diseases") OR TS=("fibrosis in lung disease") OR TS=("fibrosis in lung diseases") OR TS=("fibrosing lung disease") OR TS=("fibrosing lung diseases")) and (TS=("computed tomography") OR TS=(CT) OR TS=("magnetic resonance imaging") OR TS=(MRI) OR TS=(ultrasound) OR TS=("Positron Emission Tomography") OR TS=(PET) OR TS=("Single Photon Emission Computed Tomography") OR TS=(SPECT) OR TS=(x-ray)). The publication time span of the retrieved literature was set from January 1, 2015, to December 31, 2024, and the language was limited to English.

### *Literature Screening*

The exclusion criteria were as follows: (1) Restrictions on literature type: Non-article literature such as review articles, conference papers, book chapters, and retracted publications; (2) Literature unrelated to the topic: (a) Studies where the primary research subjects were non-pulmonary, including those where pulmonary involvement was present but the core focus was on other organs; (b) Studies that did not utilize imaging tools (e.g., CT, MRI) for analysis. After screening, a total of 1159 valid articles were obtained.

### *Literature Analysis*

Microsoft Excel 2026 was used to analyze the annual publication volume and author publication counts. CiteSpace 6.4.R1 was employed to analyze the data for publication counts by country/region, journal publication volume, keyword co-occurrence, and citation burst detection. VOSviewer 1.6.20 was utilized to perform highly-cited analysis and co-citation analysis on the data. Scimago Graphica was used to generate the international collaboration network map.

## Results

### *Publication volume analysis*

A total of 3,071 records were retrieved, and 1,159 articles were included in the analysis. Annual statistics show that publication volume exhibited an overall linear growth trend (R2 = 0.8674) (Figure 2).

### *Countries/regions research output and collaboration network*

Researchers from 64 countries/regions participated; the top ten countries by publication count contributed a combined total of 1,246 occurrences (including duplicates from international collaborations), accounting for 78.61% of all country participation events (Table 1). The United States (332 publications, 9,821 citations, centrality 0.3) was the most active country in terms of collaborative publications, contributing 28.65% of the total output. China (224 publications, 3,163 citations, centrality 0.09) ranked second in quantity, but its academic influence has not yet matched its production scale. Figure 3 shows the distribution of 25 core countries within the research collaboration network; the United States and the United Kingdom form the closest bilateral collaboration.

Table 1. Top 10 Countries or Regions by PF Imaging Publication Contribution (2015–2024)

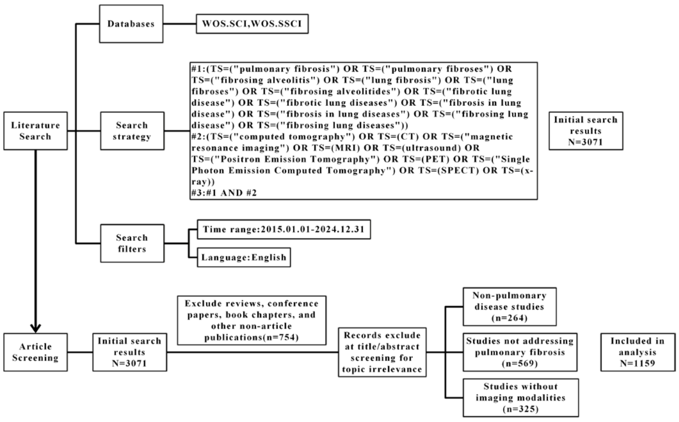
| Rank | Country/Region | Documents | Citations | Centrality |
|---|---|---|---|---|
| 1 | United States | 332 | 9821 | 0.3 |
| 2 | China | 224 | 3163 | 0.09 |
| 3 | Japan | 154 | 3599 | 0.03 |
| 4 | Italy | 132 | 3647 | 0.11 |
| 5 | United Kingdom | 112 | 4409 | 0.27 |
| 6 | Germany | 78 | 2171 | 0.12 |
| 7 | South Korea | 75 | 1082 | 0.05 |
| 8 | France | 62 | 1500 | 0.09 |
| 9 | Canada | 43 | 1136 | 0.2 |
| 10 | Netherlands | 34 | 708 | 0.02 |

Table 2. Top 10 Most Productive Cited Journals in the PF Field (2015–2024) Rank

| Rank | Journal | Publications | Journal Impact Factor |
|---|---|---|---|
| 1 | AM J RESP CRIT CARE | 888 | 19.3 |
| 2 | EUR RESPIR J | 763 | 17.0 |
| 3 | CHEST | 643 | 9.5 |
| 4 | NEW ENGL J MED | 536 | 96.3 |
| 5 | RADIOLOGY | 478 | 12.1 |
| 6 | LANCET RESP MED | 458 | 38.7 |
| 7 | THORAX | 451 | 10.8 |
| 8 | RESP RES | 391 | 4.7 |
| 9 | PLOS ONE | 380 | 2.9 |
| 10 | RESP MED | 360 | 3.5 |

Table 3. Seminal Publications Shaping PF Imaging Research

| Title | Authors | Year | Journal | Citation Burst Year |
|---|---|---|---|---|
| A multidimensional index and staging system for idiopathic pulmonary fibrosis | Brett Ley[28] | 2012 | Annals of Internal Medicine | 2015-2017 |
| Interobserver variability in the CT assessment of honeycombing in the lungs | Takeyuki Watadani[26] | 2013 | Radiology | 2015-2018 |
| Automated quantification of radiological patterns predicts survival in idiopathic pulmonary fibrosis | Fabien Maldonado[27] | 2014 | European Respiratory Journal | 2015-2018 |
| Mortality prediction in idiopathic pulmonary fibrosis: evaluation of computer-based CT analysis with conventional severity measures | Joseph Jacob[29] | 2017 | European Respiratory Journal | 2018-2022 |



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#2:(TS=("computed tomography") OR TS=(CT) OR TS=("magnetic
resonance imaging") OR TS=(MRI) OR TS=(ultrasound) OR
TS=("Positron Emission Tomography") OR TS=(PET) OR TS=("Single
Photon Emission Computed Tomography") OR TS=(SPECT) OR TS=(x-
ray))
#3:#1 AND #2
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Figure 1. Flowchart of search and screening process

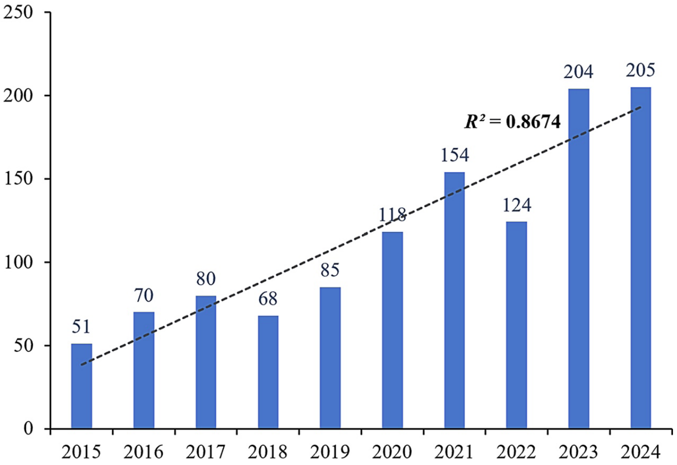


Figure 2. Bar chart of annual publications (2015–2024)

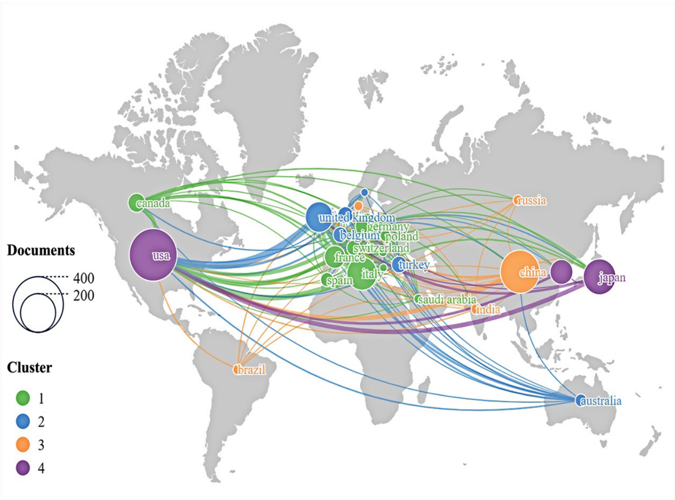


Figure 3. Geographic visualization of country collaboration network. Different node colors indicate four distinct research clusters, and connecting lines represent collaborative relationships between countries, with line thickness indicating the strength of collaboration

## *Cited journals analysis*

A total of 610 journals published research related to PF imaging. Detailed information for the top 10 journals by publication count is shown in Table 2; more than half of these cited journals have an impact factor greater than 10, indicating that the included literature has high influence and reach.

## *Author publication analysis*

Over the past decade, 442 researchers published articles in the PF field. David Lynch (30 publications, 1,603 citations, centrality 0.15) is a high-quality, high-output author who

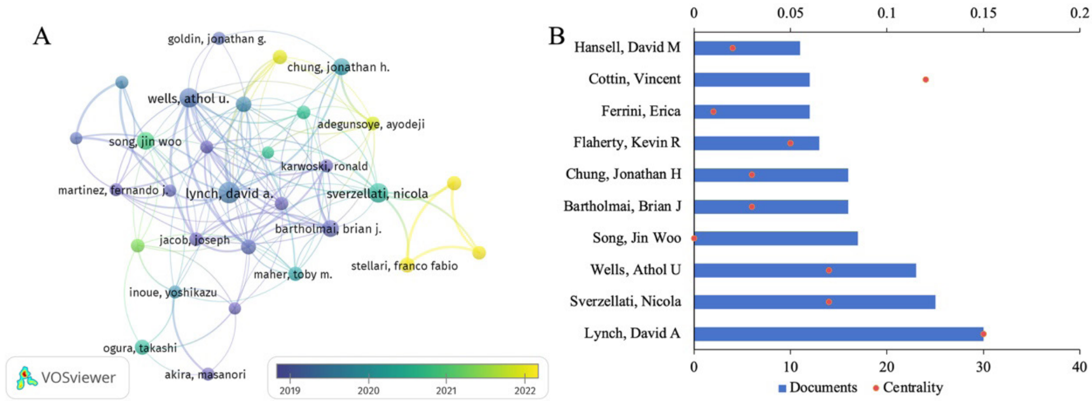
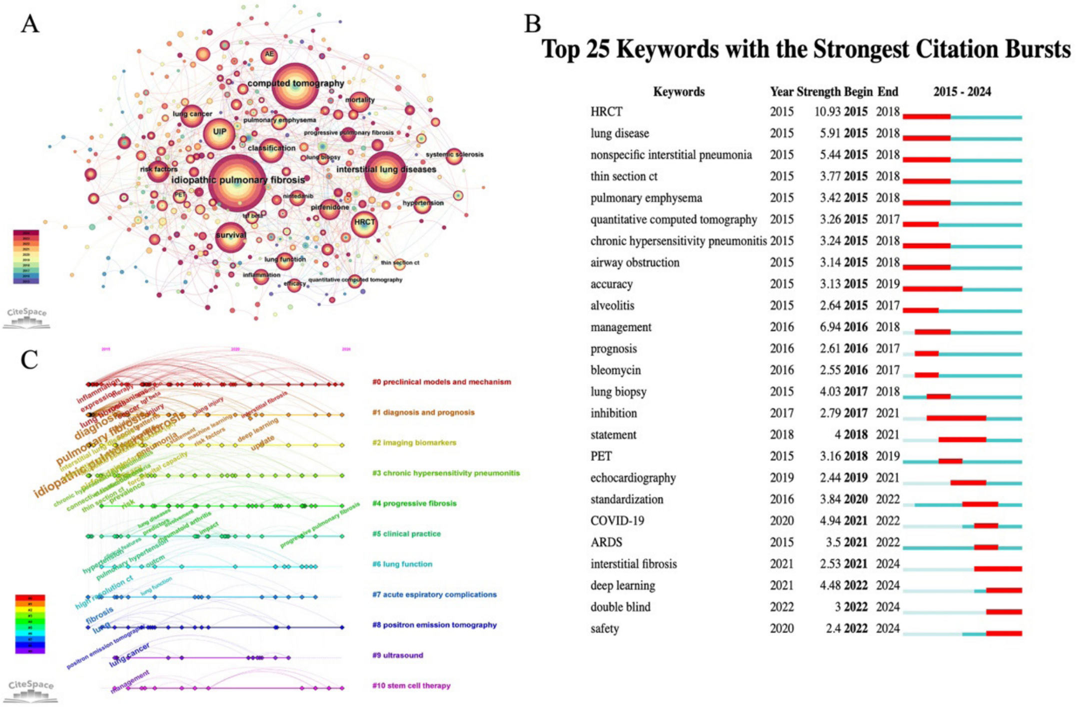


**Figure 4. Author publication analysis**



Top 25 Keywords with the Strongest Citation Bursts

| Keywords | Year | Strength | Begin | End | 2015 - 2024 |
|---|---|---|---|---|---|
| HRCT | 2015 | 10.93 | **2015** | 2018 | |
| lung disease | 2015 | 5.91 | **2015** | 2018 | |
| nonspecific interstitial pneumonia | 2015 | 5.44 | **2015** | 2018 | |
| thin section ct | 2015 | 3.77 | **2015** | 2018 | |
| pulmonary emphysema | 2015 | 3.42 | **2015** | 2018 | |
| quantitative computed tomography | 2015 | 3.26 | **2015** | 2017 | |
| chronic hypersensitivity pneumonitis | 2015 | 3.24 | **2015** | 2018 | |
| airway obstruction | 2015 | 3.14 | **2015** | 2018 | |
| accuracy | 2015 | 3.13 | **2015** | 2019 | |
| alveolitis | 2015 | 2.64 | **2015** | 2017 | |
| management | 2016 | 6.94 | **2016** | 2018 | |
| prognosis | 2016 | 2.61 | **2016** | 2017 | |
| bleomycin | 2016 | 2.55 | **2016** | 2017 | |
| lung biopsy | 2015 | 4.03 | **2017** | 2018 | |
| inhibition | 2017 | 2.79 | **2017** | 2021 | |
| statement | 2018 | 4 | **2018** | 2021 | |
| PET | 2015 | 3.16 | **2018** | 2019 | |
| echocardiography | 2019 | 2.44 | **2019** | 2021 | |
| standardization | 2016 | 3.84 | **2020** | 2022 | |
| COVID-19 | 2020 | 4.94 | **2021** | 2022 | |
| ARDS | 2015 | 3.5 | **2021** | 2022 | |
| interstitial fibrosis | 2021 | 2.53 | **2021** | 2024 | |
| deep learning | 2021 | 4.48 | **2022** | 2024 | |
| double blind | 2022 | 3 | **2022** | 2024 | |
| safety | 2020 | 2.4 | **2022** | 2024 | |

**Figure 5. Keyword analysis of research publications. (A) Co-occurrence network of keywords, with temporal information displayed as concentric rings around each node showing keyword frequency across different time periods. (B) Top 25 keywords with the strongest citation bursts, revealing emerging and intensifying research topics across different time periods from 2015 to 2024, with bar lengths indicating the duration of keyword bursts. (C) Timeline visualization of keyword evolution, displaying the chronological development and trajectories of major research topics, with different colored lines representing distinct research themes throughout the studied period**

occupies a central position in the academic network; Athol Wells (27, 1,940, 0.07) is a highly cited author with substantial academic contributions (Figure 4).

## *Keyword co-occurrence analysis*

The keyword co-occurrence network (Figure 5A) shows several densely connected clusters centered on clinical entities and imaging terms: dominant nodes include "idiopathic pulmonary fibrosis", "computed tomography/HRCT", "interstitial lung diseases", and "UIP", with secondary hubs for outcomes and treatments (e.g., "survival", "mortality", "pirfenidone") indicating tight topical coupling between diagnosis, prognosis, and therapy. The burst analysis (Figure 5B) identified the strongest recent citation bursts for imaging- and methodology-related terms — notably "deep learning" (most sustained/strongest burst through 2021–2024) — alongside earlier bursts for "HRCT", "lung disease", "interstitial fibrosis", "double blind", and "safety", reflecting shifting attention from clinical trials and safety toward advanced imaging and AI. The temporal trajectory plot (Figure 5C) illustrates thematic evolution: early years were dominated by descriptive and pathological keywords, mid-period years show growth in radiologic classification and outcome-focused terms, and the latest period marks rapid emergence of computational and machine-learning topics (deep learning, quantitative imaging), signaling a methodological transition in PF imaging research.

## *Citation trajectories of high-impact papers*

This study focused on analyzing highly cited articles from 2015 to 2024, specifically the top 1% by citation count, resulting in a total of 12 key papers. In Figure 6A, the top 50 most-cited references are displayed, highlighting pivotal works that have significantly influenced the field. Figure 6B presents co-cited references, identified through a co-citation frequency of ≥ 50, comprising 24 relevant papers. Additionally, Figure 6C outlines the 25 citation burst references, showcasing works that have experienced a significant surge in citations during specific periods. Notably, three papers appear in both the co-cited and citation-burst categories, while one paper is recognized in both the highly cited and citation-burst lists. Table 3 provides a comprehensive overview of these papers, detailing their authors, publication years, journals, and specific citation burst years.

## Discussion

Bibliometric analysis of PF imaging literature from 2015–2024 reveals a sustained increase in publication volume, reflecting the field's transition from early knowledge consolidation toward an accelerated phase centered on clinical application and decision support. Clinically, PF imaging now addresses objectives beyond morphologic pattern recognition: early identification of patients at highest risk of rapid progression; accurate HRCT pattern classification according to established diagnostic criteria (typical UIP, probable UIP, indeterminate for UIP, and alternative diagnosis); and quantitative prediction of disease trajectory and therapeutic response[17,18].

The predominant clinical challenges in IPF management are precise diagnostic classification and early risk stratification. The 2018 ATS/ERS/JRS/ALAT guideline formalized HRCT pattern-based stratification (UIP, probable UIP, indeterminate for UIP, alternative diagnosis)[7], repositioning imaging from a supportive diagnostic tool to a central element of the diagnostic algorithm; this shift is mirrored in the sustained prominence of 'UIP' and 'HRCT' as dominant keywords in the bibliometric record (Figure 5A). The 2022 update further reframed the clinical question from "Are imaging features consistent with IPF?" to "What is the patient's risk of progressive fibrosis, and when should treatment be initiated?"—a prognostication-centric reformulation[9]. The corresponding persistence of 'survival' and 'mortality' as high-frequency keywords reflects this evolution in research focus: imaging endpoints have shifted from static morphologic characterization to dynamic, outcome-linked biomarkers[19].

A parallel research frontier concerns quantitative imaging analysis and AI, particularly deep learning. The keyword 'deep learning' exhibited the strongest sustained citation burst from 2021 to 2024 (Figure 5B), signaling its transition from exploratory methodology to an established clinical application domain. Available evidence indicates that deep-learning–enabled automated segmentation and quantitative feature extraction from chest CT scan independently predict IPF progression rates and mortality risk, consistent with validated traditional quantitative measures (e.g., extent of reticulation and honeycombing)20-22. Notably, HRCT visual assessment remains subject to substantial interobserver variability; AI's principal clinical advantage lies in reproducibility, computational detection of subtle longitudinal change, and institution-independent pattern recognition. Clinical translation depends on resolving algorithmic interpretability constraints, mitigating training-data bias, demonstrating multicenter validity, and achieving integration within structured reporting workflows[23]. The greatest clinical utility will therefore derive from tools that reliably predict disease progression trajectories, support evidence-based treatment timing, and quantify antifibrotic response—not from maximizing model complexity or classification accuracy per se[13].

Citation-trajectory analysis (Figure 6) across the past decade identifies three temporally overlapping phases in PF research: diagnostic and staging framework consolidation (approximately 2015–2018), a computational turn in CT-based phenotyping (2016–2022), and therapeutic expansion toward antifibrotics and progressive fibrosing Interstitial Lung Disease (PFILD) (2019–2024). Landmark guideline documents and randomized controlled trial publications generated the largest citation bursts, establishing diagnostic consensus and affirming antifibrotic efficacy, thereby reorienting the citation network around mechanistic and clinical trial evidence[24,25]. Simultaneously, studies documenting interobserver variability in honeycombing and validating automated CT pattern quantification drove a transition from qualitative toward quantitative radiology[26]; machine-learning CT metrics progressively outperformed conventional severity indices in mortality prediction, with direct implications for disease monitoring, trial stratification, and regulatory endpoints[27]. Co-citation structure reveals strong interconnections among guideline, therapeutic, and HRCT literatures; the Gender, Age, and Physiology (GAP) index, by contrast, remained relatively isolated, suggesting delayed integration of clinical staging tools with radiological quantification methods[12,28]. Citation bursts from 2020 to 2024 centered on PFILD and nintedanib reflect a conceptual reframing of IPF as one point on a mechanistic continuum of fibrotic lung disease rather than a discrete clinical entity[24,25]. Research priorities expected to gain traction include translating AI-driven CT phenotyping into real-time progression and treatment-response assessment tools; prospective cohort studies to differentiate truly progressive non-IPF ILDs and validate predictive biomarkers; multi-omics and circulating biomarker integration with imaging for precision prognostication; and greater incorporation of patient-reported outcomes into trial endpoints. Collectively, these trajectories reflect a field that has moved beyond guideline-anchored consensus toward mechanistic and computational diversification; the central challenge now is translating these gains into individualized, clinically actionable strategies across the fibrotic lung disease spectrum.

Collaboration network analysis identifies four distinct research clusters (Figure 3), each representing a regionally organized research community with characteristic within-group connectivity and between-group engagement. Cluster 1 (Western Europe–North America axis, largest node size) demonstrates dense institutional interconnections and high cumulative publication volume, indicative of mature, well-established partnerships and multicenter trial infrastructure. Clusters 2, 3, and 4 (representing Asian-Pacific, secondary European, and emerging research nodes, respectively) show lower internal density and sparse bridges to Cluster 1, suggesting either early-stage research ecosystems or language and institutional barriers that limit cross-cluster visibility. The overall sparsity of inter-cluster connections indicates that PF imaging research remains geographically fragmented, with limited evidence of systematic global data-sharing or coordinated multicenter study design. This fragmentation carries substantive methodological risk: deep learning models trained on single-institution datasets or regionally constrained cohorts are susceptible to algorithmic bias, reduced cross-population generalizability, and failure to meet validation standards required for international guideline endorsement and clinical deployment. Progress in quantitative imaging and AI—the field's primary research frontier—therefore depends on establishing cross-cluster collaboration frameworks, shared imaging repositories, and standardized HRCT acquisition and reporting protocols to support reproducible, bias-mitigated model development.

## Limitation

The data source of this study is limited to the Web of Science Core Collection, which may restrict the breadth and depth of literature coverage. Moreover, only English-language original research results were included, potentially omitting non-English high-quality research findings from other databases. Additionally, bibliometric and quantitative indicators (such as citation frequency and impact factors) are subject to discipline size and temporal effects, which may not fully reflect research quality. The heterogeneity of different research types and methodologies may further limit the comparability of certain bibliometric comparisons. It is recommended that future studies incorporate multiple databases, such as Scopus and MEDLINE, for cross-validation and employ complementary qualitative methods to more comprehensively evaluate research contributions beyond traditional citation metrics.

## Conclusions

PF imaging research has shifted from diagnostic consensus toward quantitative and computational methods, with deep learning and quantitative CT biomarkers now constituting the field's primary investigative frontier—driven by the clinical imperative to overcome HRCT classification variability and enable individualized risk prediction. Geographic research fragmentation and limited multicenter validation remain the principal threats to AI generalizability and clinical deployment. Addressing these barriers requires coordinated international collaboration frameworks, standardized imaging protocols, and prospective validation cohorts to translate algorithmic advances into bias-mitigated, precision-guided clinical strategies across the fibrotic lung disease spectrum.

## Statements and declarations

### *Author contributions*

## Funding sources

## Competing interests

The authors have no relevant financial or non-financial interests to disclose.

## Data availability statement

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

## Ethics approval

This study is a bibliometric analysis based entirely on publicly available literature data from Web of Science Core Collection. As no human or animal subjects were involved, and no personal sensitive information was used, ethical approval was not required for this research.

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**Table 5. Comparison of the mean scores the pregnant women obtained from the PIKQ and UIAS in terms of some variables (n= 255)**

| | PIKQ | | UIAS | |
|---|---|---|---|---|
| Variables | Mean±SD | p-value | Mean±SD | p-value |
| Age | | | | |
| <30 | 8.12±2.79 | 0.73 | 42.34±3.33 | 0.96 |
| ≥30 | 8.01±2.45 | | 42.32±3.66 | |
| Education Status | | | | |
| Primary school | 6.86±2.84 | 0.00[b] | 41.37±3.15 | 0.00[b] |
| High school | 8.16±2.67 | | 42.31±3.48 | |
| University and above | 8.90±2.10 | | 43.05±3.57 | |
| Gravida | | | | |
| Primigravida | 8.14±2.78 | 0.47 | 43.18±3.26 | 0.94 |
| Multigravida | 8.03±2.55 | | 41.80±3.33 | |
| Parity | | | | |
| Nulliparous | 8.01±2.74 | 0.24 | 43.19±3.21 | 0.00[b] |
| Primiparous | 8.38±2.51 | | 41.97±3.39 | |
| Multiparous | 7.62±2.66 | | 41.21±3.80 | |
| UI during pregnancy (n=130) | | | | |
| Yes | 8.24±2.27 | 0.305 | 42.16±3.13 | 0.414 |
| No | 7.90±2.98 | | 42.52±3.81 | |
| Pregnant women presenting to healthcare services with a complaint of UI (n=130) | | | | |
| Yes | 8.20±2.38 | 0.882 | 42.88±3.94 | 0.059 |
| No | 8.26±2.22 | | 41.79±2.57 | |

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