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editorial-office@sciformat.ca

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ARTIFICIAL INTELLIGENCE IN THE DIAGNOSIS OF OCCUPATIONAL DISEASES: TECHNOLOGICAL INNOVATIONS AND MEDICAL CERTIFICATION IN ASBESTOSIS

Kinga Głodek (Corresponding Author, Email: kingaglodek@icloud.com)

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0006-8126-0702

Julia Kalinowska

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0003-0384-230X

Kinga Kalinowska

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0002-8632-3670

Sandra Domeracka

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0009-0579-6443

Aleksandra Korny

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0005-9359-9407

Kinga Kuranc

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0002-1138-3804

Wiktoria Konecka

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0002-4900-2843

Ada Krasowska

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0008-9302-6010

Michał Bakuta

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0002-9336-9044

Karolina Dołowska

Medical University of Lublin, Lublin, Poland

ORCID ID: 0009-0004-2571-2781

ABSTRACT

Background: Asbestosis remains most significant challenges in occupational medicine. The traditional medical certification process, primarily based on the subjective visual assessment of conventional chest radiographs (CXR), is hindered by high interobserver variability. This leads to prolonged administrative disputes and delays in awarding compensation to affected workers. This review critically evaluate the impact of quantitative computed tomography (QCT) and artificial intelligence (AI) on the objectification and standardization of diagnostics and medico-legal certification in asbestosis.

Methods: A systematic literature review from 2010 to 2026 was conducted by searching the PubMed, Scopus, Web of Science, and Google Scholar databases. Publications concerning the use of machine learning algorithms, deep learning models, and advanced imaging techniques in occupational lung diseases were analyzed.

Results: The application of QCT enables the conversion of interstitial changes into measurable, objective imaging biomarkers. Meanwhile, deep learning algorithms allows for automated, high-throughput detection and staging of pulmonary fibrosis, radically accelerating the evaluation of insurance claims. However, real-world validation studies demonstrate that AI models trained on historical diagnoses can replicate the errors of human experts. Furthermore, the "black box" nature of these algorithms poses ethical and legal challenges, blurring diagnostic accountability.

Conclusions: The fusion of AI and QCT represents a breakthrough toward fair and objective medical certification. Nevertheless, due to ethical and cognitive dilemmas, full automation of this process is currently unjustified. The priority remains the development of explainable artificial intelligence systems and the implementation of hybrid models, where automated analysis supports the final decisions of reduced expert panels.

KEYWORDS

Asbestosis, Occupational Medicine, Artificial Intelligence, Quantitative Computed Tomography, Deep Learning

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1. Introduction

Asbestosis remains one of the most thoroughly documented occupational diseases associated with exposure to industrial dust, representing a significant public health issue and a complex challenge for medical certification. Although the use of asbestos has been restricted or completely banned in many countries, the consequences of its historical, long-term utilization remain profoundly visible. According to the definitive position of the World Health Organization (WHO), all forms of asbestos are classified as pathogenic, and their inhalation leads to irreversible respiratory tract disorders, including chronic asbestosis and malignancies. Occupational asbestos exposure accounts for over 200,000 deaths globally each year, contributing to more than 70% of all deaths caused by occupational cancers [1]. Concurrently, asbestos-related diseases remain a leading cause of work-related mortality, particularly in industrialized nations where asbestos was extensively used in construction and manufacturing for decades [2].

Asbestosis is a chronic interstitial lung disease that develops as a result of prolonged inhalation of asbestos fibers. From a clinical perspective, the development of fully symptomatic fibrosis typically requires 10 to 20 years of direct occupational exposure [3]. This extended latency period constitutes one of the most critical diagnostic and legal challenges. In practice, former workers often lack comprehensive employment records, making the reconstruction of historical occupational exposure conditions difficult or impossible after several decades [2]. An additional complicating factor is the frequent coexistence of other respiratory diseases, such as chronic obstructive pulmonary disease or smoking-related changes, which can confound the definitive interpretation of both clinical and radiological presentations [3].

The severity of this issue is further corroborated by epidemiological data. The Global Burden of Disease Study 2021 demonstrated that pneumoconioses continue to impose a substantial health burden worldwide. In 2021, over 10,000 new cases of asbestosis and more than 3,000 associated deaths were recorded globally [4]. Crucially, the authors of the study highlighted that, unlike other occupational pneumoconioses, the incidence

and prevalence rates of asbestosis exhibit a continuous upward trend, particularly among men and older populations [4]. Furthermore, global analyses of work-related disease and injury burdens indicate that occupational illnesses currently account for a substantially higher number of deaths than workplace injuries [5]. These data underscore that the long-term consequences of occupational exposure to industrial dust remain a severe social and economic burden.

In Poland, this problem primarily affects former workers in asbestos processing plants, shipbuilding, and the construction industry. Surveillance studies conducted among cohorts of former asbestos workers demonstrate a persistent prevalence of pathological changes many years after the cessation of occupational exposure [6]. It is also essential to emphasize that asbestos exposure correlates not only with the risk of developing asbestosis but also with highly aggressive malignancies, most notably malignant pleural mesothelioma. It is estimated that the actual mortality rate associated with mesothelioma may be significantly underestimated due to incomplete epidemiological reporting and diagnostic limitations encountered in multiple countries [7]. Consequently, administrative proceedings aimed at recognizing asbestos-related conditions as occupational diseases frequently degenerate into prolonged legal disputes regarding the entitlement to financial compensation, disability pensions, and indemnity benefits.

A major institutional effort to address the inherent subjectivity in medical certification involves the deployment of systemic health surveillance programs, such as the comprehensive model designed and implemented in the Tuscany region of Italy. These programs rely on highly structured monitoring protocols for former asbestos-exposed workers, thereby standardizing diagnostic criteria and minimizing the reliance of the evaluation process on the individual experience of the certifying physician [8]. By integrating a rigorous analysis of exposure history with standardized clinical evaluations, such initiatives enhance the detection of pathological changes during preclinical stages and ensure greater reproducibility of medical assessments, which is paramount for the equitable allocation of compensation benefits [8,9].

In recent years, artificial intelligence (AI) technologies have gained increasing prominence in the diagnosis of pulmonary diseases. Machine learning and deep learning algorithms are currently being utilized for the automated analysis of computed tomography scans and chest radiographs, enabling the detection of subtle interstitial abnormalities and significantly improving diagnostic reproducibility. Within the framework of occupational medicine, these solutions have the potential to mitigate the impact of subjective interpretation by clinicians and enhance the standardization of the medical certification process. However, the rapidly advancing integration of AI also raises critical questions regarding algorithmic reliability, legal accountability for diagnostic decisions, and the defined role of emerging technologies within established occupational health and medico-legal systems.

The objective of this systematic review is to analyze the current applications of AI in the diagnosis of asbestosis and to evaluate the potential impact of these advanced technologies on the medical certification process in occupational diseases. Particular emphasis is placed on the objectification of diagnostics, the reduction of human interpretative errors, and the practical utility of AI-driven tools in contemporary occupational medicine.

2. Methodology

Study Design

This paper was prepared as a review article aimed at a critical synthesis of the current state of knowledge regarding the application of AI and quantitative computed tomography (QCT) in the diagnosis of asbestosis. The adopted research model focuses on analyzing the impact of advanced imaging technologies on the objectification and standardization of medical certification in occupational diseases.

Data Collection

The identification of relevant literature was performed using leading databases: PubMed, Scopus, Web of Science, and Google Scholar. The data collection process was conducted between March and April 2026. The chronological timeframe of the analysis primarily covered publications released from 2014 to 2026, which allowed for capturing key breakthroughs in the fields of machine learning algorithms and advanced radiological diagnostics. The search strategy was based on the following keywords: *asbestosis*, *artificial intelligence*, *machine learning*, *occupational health*, *medico-legal*, *quantitative computed tomography*, *diagnostic imaging*, combined using the Boolean operators "AND" and "OR". Full-text original research

articles, review papers, and reports from international organizations, including the World Health Organization (WHO), the International Labour Organization (ILO), and the Global Burden of Disease (GBD) study, were included in the analysis. Case reports, conference abstracts, and publications with insufficient methodological quality were excluded.

Analysis Techniques

A method of qualitative and comparative data analysis was applied, focusing on three thematic pillars: a critical analysis of the limitations of conventional radiography, an evaluation of the utility of QCT parameters, and an assessment of the efficacy of automated AI systems in categorizing pathological changes along with their potential to minimize legal and administrative disputes in compensation proceedings.

3. Results

3.1 Challenges of Conventional Diagnostic Imaging in Medical Certification

For decades, conventional chest radiography (CXR) has remained the primary tool utilized in screening and diagnosing asbestos-related diseases. Although this method is universally accessible, cost-effective, and easy to perform, it is characterized by significant limitations, particularly in the early detection of interstitial changes. Conventional CXR scans frequently fail to visualize subtle pathologies in the initial stages of the disease, which often delays proper diagnosis and the implementation of appropriate surveillance [9]. The superiority of more modern imaging modalities in this regard has been corroborated by numerous comparative studies. The application of high-resolution computed tomography (HRCT) allows for a significantly more precise differentiation of asbestosis from other disorders with a similar clinical presentation, such as fibrosing hypersensitivity pneumonitis [10]. However, given that standard computed tomography involves a substantial ionizing radiation burden, which poses a significant concern for regular screening programs, it became necessary to seek safer alternatives. The use of ultra-low-dose computed tomography drastically reduces radiation exposure while maintaining high diagnostic performance in detecting pleuropulmonary changes. This makes the modality an optimal and safe tool for the long-term monitoring of asbestos-exposed workers [11].

A critical challenge in the medical certification process, however, is not solely the technological imperfection of the imaging modality itself, but primarily the subjective human factor involved in its evaluation. Errors and discrepancies in radiology represent an inevitable element of daily clinical practice and are rarely evidence of direct medical negligence. They stem from natural human limitations within a complex diagnostic process. Notably, the vast majority of mistakes, up to 60–80%, consist of so-called perceptual errors, which involve failing to notice an existing abnormality, and cognitive errors, resulting from the incorrect interpretation of visualized changes [12]. In occupational medicine, the main weakness of traditional CXR scans and the widely used ILO International Classification of Radiographs of Pneumoconioses remains the high rate of human error and interobserver variability. Assessments of the same radiographs performed by different, even highly specialized experts, can be divergent. Within the framework of occupational compensation proceedings, such interpretative differences generate immense legal and social problems, calling into question the reliability of compensation processes [13].

In response to these difficulties, the medical community has undertaken successful attempts to standardize and digitalize the ILO reference images, aiming to improve the consistency and reproducibility of assessments [14]. It must be emphasized, however, that a digital radiological image remains merely a two-dimensional projection of anatomical structures, which ultimately must be interpreted by a human being. This challenge remains relevant even in advanced stages of dust-related diseases. Research into the morphology of progressive massive fibrosis in modern dust-exposed workers has confirmed that the radiological patterns they present are consistent with classic textbook definitions, which theoretically should facilitate diagnosis. Nevertheless, despite this consistency of patterns, substantial interobserver variability is still observed in certification practice among experts classifying the same radiographs [15]. This persistent difficulty in achieving full consensus using visual methods defines the limits of conventional radiography's utility and necessitates the implementation of more objective tools, such as quantitative computed tomography and machine learning algorithms.

3.2 Quantitative Computed Tomography as a Foundation for Objectification

In response to the perceptual limitations of conventional diagnostics, methods based on advanced numerical analysis are being deployed in occupational medicine. Quantitative computed tomography enables a transition from subjective visual assessment toward the precise determination of changes within the lung parenchyma. This technology allows for the conversion of a three-dimensional image of the organ's structure into measurable digital data through densitometric analysis at the single-voxel level. This enables the precise calculation of the volume of fibrotic tissue, total lung capacity, and the percentage degree of parenchymal destruction. In certification processes, these parameters serve as an objective indicator of clinical status, thereby reducing the risk of decisional discrepancies arising from interobserver variability.

Quantitative methods demonstrate particular utility in diagnosing the early stages of occupational diseases. High-resolution computed tomography analyses confirm the high application value of density measurements in identifying early pneumoconiotic changes and coexisting conditions. These tools allow for catching subtle parenchymal pathologies during the preclinical stage, which is of paramount importance for prevention and the prompt cessation of occupational exposure [16]. Furthermore, the development of computational methods has enabled the isolation of specific imaging biomarkers. Utilizing validated three-dimensional indices allows for the automated identification of pneumoconiotic changes, standardizing the diagnostic process and rendering it independent of the individual clinician's subjective experience [17].

From the perspective of compensation and insurance systems, a single confirmation of the presence of the disease is often insufficient for the equitable determination of an appropriate amount of disability pension benefits. In the certification process, it is crucial to precisely monitor the dynamics of fibrotic progression and to demonstrate its direct translation into escalating organ insufficiency. Critical data in this aspect are provided by longitudinal studies utilizing HRCT. The applied methodology proves that modern algorithms can objectively correlate progressive structural changes in the lung tissue with the degree of respiratory function impairment and the patient's overall clinical presentation [18]. The capacity for continuous, numerical tracking of disease progression provides medical boards with indisputable arguments during the periodic updating of certifications regarding the percentage of impairment to health.

Concurrently, radiomics represents the highest level of advancement in quantitative analysis, based on the automated extraction of hundreds of geometric and textural features from tomographic images. Machine learning models that integrate radiomic data with occupational health surveillance registries allow for the precise prediction of preclinical stages and the creation of a worker's digital health profile [19]. The fusion of QCT parameters with analytical tools enhances the transparency of the certification process, offering insurance institutions and the judicial system a reliable basis for evaluating compensation claims.

3.3 Artificial Intelligence Algorithms in Diagnostic Automation

The introduction of AI, particularly deep learning algorithms, represents a major turning point in the diagnosis of occupational diseases, transforming the established manner of interpreting medical images. Despite the growing role of computed tomography, conventional radiography remains the dominant tool in mass screening programs due to its accessibility and lower costs. In this domain, AI algorithms serve as an advanced support system, increasing the diagnostic value of traditional chest radiographs. Utilizing deep convolutional neural networks enables the creation of precise triage systems capable of automatically detecting early interstitial changes in large populations of workers exposed to hazardous dust [20].

From a certification perspective, accurately staging the disease is just as critical as its initial detection. This presents a challenge due to the clinical ambiguity of boundaries between stages and historical errors within archives that distort the model training process. To address this, a cascaded deep learning paradigm was developed, combining segmentation with proper staging. This architecture effectively eliminates the problem of model overfitting, achieving an overall classification accuracy of 90.4%. Crucially for occupational medicine, the algorithm exhibits 76.5% sensitivity and 95% specificity in identifying the early stages of pneumoconiosis [21]. These technologies are currently evolving toward multi-stage systems that optimize simultaneous diagnosis and the assessment of fibrotic progression [22].

In advanced diagnostics based on QCT, the integration of advanced algorithms significantly enhances diagnostic accuracy. However, the primary challenge within the framework of occupational medicine remains the "black box" problem, which limits the capacity of physicians and courts to substantively verify a certification. Consequently, prioritizing the deployment of methods that increase the interpretability and explainability of AI-generated results is imperative. Moreover, the higher resolution of computed tomography necessitates an evolution of diagnostic standards. It is postulated that in algorithmic evaluation, the traditional

ILO classification should be replaced by the ICOERD system, allowing for a tool standardization more closely grounded in clinicopathological correlation [23].

However, the verification of AI algorithms under real-world certification conditions reveals substantial challenges associated with their implementation. The prospective PROSBEST study, evaluating the efficacy of an automated system in a cohort of applicants seeking financial compensation for asbestosis, demonstrated that the model failed to achieve its predefined validation criteria. The observed drop in algorithmic performance under clinical conditions is attributed to the high interobserver variability within the reference expert panel. Because machine learning models are trained on diagnoses established by clinicians, this phenomenon leads to the generation of "noisy labels" within datasets, directly undermining system reliability [24]. These findings prove that AI in its current state cannot function as a fully autonomous arbiter in compensation proceedings. Deploying this technology into certification practice requires prior objectification of reference standards, such as through QCT quantitative segmentation. Furthermore, it necessitates the adaptation of a hybrid approach, where the algorithm does not replace the entire medical board but functions as a peer entity supporting the classic expert panel.

4. Discussion

The application of AI extends far beyond diagnostic imaging alone, redefining the global approach to occupational health and safety. The implementation of these tools is of particular significance in developing countries, among other regions, where a critical shortage of radiologists delays medical certification processes [25]. Furthermore, algorithms enable a transition from reactive diagnosis to proactive prevention. Automated analysis of environmental and equipment conditions allows for real-time hazard identification and the deployment of protective measures before harmful dust exposure occurs [25,26]. However, it is essential to note that implementing such innovations in the workplace requires a careful balance between technological progress, respect for workers' rights, and rigorous data privacy protection [26].

The social dimension of this digital transformation is particularly vital within the context of an aging population and the insufficiency of traditional medical certification boards. Utilizing AI algorithms as automated support allows for the rapid evaluation of compensation claims from former industrial workers. As researchers indicate, the application of AI effectively mitigates administrative bottlenecks stemming from difficulties in establishing a definitive diagnosis, thereby radically shortening the processing time for benefits [25].

Despite these undeniable benefits, the full automation of occupational medicine raises fundamental ethical and cognitive dilemmas. The medical community faces a significant challenge: on one hand, algorithms frequently outperform human experts, yet on the other hand, they introduce a high degree of uncertainty into the certification process. Deferring diagnostics to machines leads to a blurring of the boundaries of legal liability for potential errors. Consequently, this may promote highly risk-averse behavior among clinicians, paradoxically leading to a degradation of diagnostic quality [27].

The issue of accountability is inextricably linked to the so-called "black box" problem, algorithms that generate an output but do not explain how they arrived at it. Implementing such opaque models poses a real threat to clinical practice: physicians, fearing the legal repercussions of a potential mistake, may begin to uncritically endorse the machine's verdicts. Consequently, the patient is marginalized within the certification process, losing the opportunity to fully understand why a specific decision regarding their health was made. To prevent blind faith in technology, the development of explainable AI systems becomes a priority. Algorithmic transparency is essential for the equitable allocation of compensation benefits and to ensure that the patient, rather than the IT system, remains the central focus of occupational medicine [28]. Additionally, prospective validations prove that under real-world conditions, AI models can replicate errors stemming from the historical diagnoses of human certifiers, which excludes them from serving as fully autonomous arbiters [24].

The aforementioned ethical dilemmas, however, do not constitute an argument for disqualifying AI from occupational medicine. It must be emphasized that decision-making processes involving solely the human factor are equally prone to reasoning errors and uncertainty [27]. The optimal direction of development remains the implementation of hybrid models. Integrating automated imaging analysis with rigorous oversight by streamlined expert panels allows for the maximization of technological benefits while preserving the physician's ethical and legal responsibility for the patient.

5. Conclusions

The introduction of advanced imaging technologies, such as QCT and AI algorithms, represents a fundamental step toward objectifying medical certification in asbestos-related diseases. These tools effectively minimize the problem of interobserver variability, which is the primary weakness of conventional radiography and traditional visual expert assessments. Translating subjective clinical impressions into measurable, mathematical values of percentage lung parenchymal damage enhances the transparency and reliability of compensation procedures.

The utilization of automated diagnostic tools enables high-throughput screening of documentation and precise staging of fibrotic progression. This contributes to a radical acceleration of compensation proceedings, which is of paramount social importance given the aging population of former asbestos-exposed workers. Furthermore, the deployment of AI facilitates a shift toward proactive occupational risk management, supporting the identification of environmental hazards before harmful exposure occurs.

Despite high technological efficacy, the complete automation of medical certification processes at the current stage of development is unjustified from both medical and ethical standpoints. The problem of the algorithmic "black box," the blurring of legal liability for potential errors, and the proven susceptibility of machine learning models to replicate mistakes from historical databases disqualify AI from serving as a fully autonomous arbiter. Addressing these challenges requires the development of explainable artificial intelligence systems that guarantee the transparency of the decision-making pathway.

The optimal evolutionary model for occupational medicine remains the implementation of a hybrid approach. Integrating automated, unbiased imaging analysis with rigorous oversight by streamlined expert panels maximizes technological advantages while maintaining the clinician's ethical and legal responsibility for the patient. The multifaceted integration of these solutions enables the creation of a modern, efficient, and equitable occupational benefits system.

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REFERENCES

1. World Health Organization. (2024, September 27). Asbestos. <https://www.who.int/news-room/fact-sheets/detail/asbestos>
2. Thives, L. P., Ghisi, E., Thives Júnior, J. J., & Vieira, A. S. (2022). Is asbestos still a problem in the world? A current review. *Journal of Environmental Management*, 319, 115716. <https://doi.org/10.1016/j.jenvman.2022.115716>
3. Bhandari, J., Thada, P. K., & Sedhai, Y. R. (2022). Asbestosis. In *StatPearls*. StatPearls Publishing. <https://www.ncbi.nlm.nih.gov/books/NBK555985/>
4. Shen, J., Wang, J., Zhang, B., Li, P., Han, R., Zhou, S., & Wang, R. (2025). Global, regional, and national burden of pneumoconiosis caused by different etiologies: An update from the Global Burden of Disease Study 2021. *Respiratory Medicine*, 249, 108480. <https://doi.org/10.1016/j.rmed.2025.108480>
5. Takala, J., Hämäläinen, P., Sauni, R., Nygård, C. H., Gagliardi, D., & Neupane, S. (2024). Global-, regional- and country-level estimates of the work-related burden of diseases and accidents in 2019. *Scandinavian Journal of Work, Environment & Health*, 50(2), 73–82. <https://doi.org/10.5271/sjweh.4132>
6. Świątkowska, B. (2019). The occurrence of asbestos-related diseases among former employees of asbestos processing plants in Poland. *Medycyna Pracy*, 70(6), 723–731. <https://doi.org/10.13075/mp.5893.00890>
7. Odgerel, C. O., Takahashi, K., Sorahan, T., Driscoll, T., Fitzmaurice, C., Yoko-O, M., Sawanyawisuth, K., Furuya, S., Tanaka, F., Horie, S., Zandwijk, N. V., & Takala, J. (2017). Estimation of the global burden of mesothelioma deaths from incomplete national mortality data. *Occupational and Environmental Medicine*, 74(12), 851–858. <https://doi.org/10.1136/oemed-2017-104298>

8. Chellini, E., Battisti, F., Cristaudo, A., Sartorelli, P., & Calà, P. (2018). Health surveillance for former asbestos exposed worker: A specific programme developed in an Italian region. *Journal of Thoracic Disease*, 10(Suppl 2), S383–S389. <https://doi.org/10.21037/jtd.2017.10.84>
9. Santos, U. P., Algranti, E., Capitani, E. M., Prado, G. F., Carneiro, A. P. S., Rodrigues, S. C. S., Freitas, J. B. P., Chate, R. C., Mizutani, R. F., Castro, H. A., Arbex, M. A., Ribeiro, P. C., Tietboehl Filho, C. N., Castellano, M. V. C. O., Leite, G. W., Almeida, G. C., & Committee on Environmental and Occupational Diseases. (2024). Brazilian Thoracic Society recommendations for the diagnosis and monitoring of asbestos-exposed individuals. *Jornal Brasileiro de Pneumologia*, 50(3), e20240156. <https://doi.org/10.36416/1806-3756/e20240156>
10. Ma, R., Li, S., Wang, Y., Yang, S., Bao, N., & Ye, Q. (2022). High-resolution computed tomography features of asbestosis versus fibrotic hypersensitivity pneumonitis: An observational study. *BMC Pulmonary Medicine*, 22(1), 207. <https://doi.org/10.1186/s12890-022-01967-3>
11. Schaal, M., Severac, F., Labani, A., Jeung, M. Y., Roy, C., & Ohana, M. (2016). Diagnostic performance of ultra-low-dose computed tomography for detecting asbestos-related pleuropulmonary diseases: Prospective study in a screening setting. *PLOS One*, 11(12), e0168979. <https://doi.org/10.1371/journal.pone.0168979>
12. Brady, A. P. (2017). Error and discrepancy in radiology: Inevitable or avoidable? *Insights into Imaging*, 8(1), 171–182. <https://doi.org/10.1007/s13244-016-0534-1>
13. Halldin, C. N., Blackley, D. J., Petsonk, E. L., & Laney, A. S. (2017). Pneumoconioses radiographs in a large population of U.S. coal workers: Variability in A reader and B reader classifications by using the International Labour Office classification. *Radiology*, 284(3), 870–876. <https://doi.org/10.1148/radiol.2017162437>
14. Halldin, C. N., Petsonk, E. L., & Laney, A. S. (2014). Validation of the International Labour Office digitized standard images for recognition and classification of radiographs of pneumoconiosis. *Academic Radiology*, 21(3), 305–311. <https://doi.org/10.1016/j.acra.2013.11.019>
15. Halldin, C. N., Blackley, D. J., Markle, T., Cohen, R. A., & Laney, A. S. (2020). Patterns of progressive massive fibrosis on modern coal miner chest radiographs. *Archives of Environmental & Occupational Health*, 75(3), 152–158. <https://doi.org/10.1080/19338244.2019.1593099>
16. Hu, X., Liu, X. D., Gao, T., & Guo, Q. (2025). The application value of HRCT quantitative analysis in early pneumoconiosis and concomitant diseases. *Medicine*, 104(18), e42374. <https://doi.org/10.1097/MD.00000000000042374>
17. Pyo, J., Chau, N. K., Park, E. K., & Choi, S. (2023). Computed tomography-based imaging biomarker identifies coal workers' pneumoconiosis. *Frontiers in Physiology*, 14, 1288246. <https://doi.org/10.3389/fphys.2023.1288246>
18. Chau, N. K., Park, E. K., & Choi, S. (2025). Longitudinal analysis of coal workers' pneumoconiosis using enhanced resolution-computed tomography images: Unveiling patterns in lung structure, function, and clinical correlations. *Frontiers in Physiology*, 16, 1578058. <https://doi.org/10.3389/fphys.2025.1578058>
19. Ma, Y., Cui, F., Yao, Y., Shen, F., Qin, H., Li, B., & Wang, Y. (2025). Machine learning models for the prediction of preclinical coal workers' pneumoconiosis: Integrating CT radiomics and occupational health surveillance records. *Journal of Translational Medicine*, 23(1), 896. <https://doi.org/10.1186/s12967-025-06907-3>
20. Li, X., Xu, M., Yan, Z., Xia, F., Li, S., Zhang, Y., Xing, Z., & Guan, L. (2024). Deep convolutional network-based chest radiographs screening model for pneumoconiosis. *Frontiers in Medicine*, 11, 1290729. <https://doi.org/10.3389/fmed.2024.1290729>
21. Sun, W., Wu, D., Luo, Y., Liu, L., Zhang, H., Wu, S., Zhang, Y., Wang, C., Zheng, H., Shen, J., & Luo, C. (2022). A fully deep learning paradigm for pneumoconiosis staging on chest radiographs. *IEEE Journal of Biomedical and Health Informatics*, 26(10), 5154–5164. <https://doi.org/10.1109/JBHI.2022.3190923>
22. Liu, C., Fang, Y., Xie, Y., Zheng, H., Li, X., Wu, D., & Zhang, T. (2024). Deep learning pneumoconiosis staging and diagnosis system based on multi-stage joint approach. *BMC Medical Imaging*, 24(1), 165. <https://doi.org/10.1186/s12880-024-01337-x>

23. Suganuma, N., Tamura, T., & Eitoku, M. (2026). Artificial intelligence in quantitative chest imaging analysis for occupational lung disease: Appraisal of its current status. *Current Opinion in Pulmonary Medicine*, 32(2), 142–146. <https://doi.org/10.1097/MCP.0000000000001240>
24. Smesseim, I., Lipman, K. B. W. G., Trebeschi, S., Stuiver, M. M., Tissier, R., Burgers, J. A., & de Gooijer, C. J. (2025). Prospective validation of an artificial intelligence assessment in a cohort of applicants seeking financial compensation for asbestosis (PROSBEST). *European Radiology Experimental*, 9(1), 76. <https://doi.org/10.1186/s41747-025-00619-5>
25. Shah, I. A., & Mishra, S. (2024). Artificial intelligence in advancing occupational health and safety: An encapsulation of developments. *Journal of Occupational Health*, 66(1), uiad017. <https://doi.org/10.1093/joccuh/uiad017>
26. El-Helaly, M. (2024). Artificial intelligence and occupational health and safety, benefits and drawbacks. *La Medicina del Lavoro*, 115(2), e2024014. <https://doi.org/10.23749/mdl.v115i2.15835>
27. Grote, T., & Berens, P. (2020). On the ethics of algorithmic decision-making in healthcare. *Journal of Medical Ethics*, 46(3), 205–211. <https://doi.org/10.1136/medethics-2019-105586>
28. Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V. I., & Precise4Q Consortium. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, 20(1), 310. <https://doi.org/10.1186/s12911-020-01332-6>