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Transformative role of artificial intelligence in enhancing occupational health and safety: A systematic review and meta-analysis

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ABSTRACT

Objectives: This study aims to systematically review and analyze the impact of artificial intelligence (AI) technologies on occupational health and safety (OHS), focusing on their effectiveness in risk mitigation, disease prevention, and the promotion of worker well-being.

Methods: A comprehensive literature search was conducted across databases including Embase, PubMed, and Google Scholar, covering studies from 1974 to the present. The review followed the guidelines set forth by Cochrane, with data analyzed using the Review Manager software (Version 5.4).

Results: The analysis included 25 studies involving diverse industries, with a total of 2,500 workers. Findings indicated a significant positive effect of AI technologies on reducing occupational hazards (SMD: -0.75, 95% CI: -0.82 to -0.68, Z=18.45, P<0.00001) and enhancing safety protocols (SMD: -0.45, 95% CI: -0.56 to -0.34, Z = 9.30, P<0.00001). Furthermore, AI-driven monitoring tools were associated with a notable decrease in workplace accidents (SMD: -0.52, 95% CI: -0.60 to -0.44, Z = 14.23, P<0.00001).

Conclusions: The integration of AI in occupational health and safety practices significantly enhances the management of workplace risks, leading to improved safety outcomes and reduced incidents. This study underscores the need for continued investment in AI technologies to promote healthier and safer work environments.

Keywords: Artificial intelligence, occupational health and safety, risk management, workplace safety, systematic review, meta-analysis

Occupational health and safety (OHS) is a fundamental concern across all sectors, prioritizing the well-being of employees for both ethical and operational reasons. Effective OHS measures not only safeguard the health and protection of workers but also enhance workplace efficiency and productivity. The industrial landscape is fraught with hazards, many of which can lead to acute or chronic occupational diseases. Respiratory diseases, particularly those associated with the inhalation of hazardous substances such as coal dust, silica, asbestos, aluminum, cotton, lead, and beryllium, are among the most commonly diagnosed work-related conditions [1]. Conditions such as coal workers' pneumoconiosis (CWP), silicosis, and asbestosis have long been recognized as serious risks for workers exposed to harmful dust and fibers, especially in high-risk industries like mining, construction, and manufacturing.

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The global prevalence of occupational diseases affects both developed and developing nations. Despite improvements in safety standards over recent decades, the burden of occupational diseases and accidents remains a major public health concern. Lower to middle-income countries, such as Russia, China, and India, often struggle to implement and enforce comprehensive OHS policies due to economic constraints and industrialization pressures [2]. However, these challenges are not confined to these regions, as higher-income countries also face difficulties, particularly in industries where hazardous materials or high-risk conditions are prevalent [3, 4]. The economic ramifications of inadequate OHS measures are substantial, with poor occupational safety and health conditions estimated to account for 4% to 5% of the gross domestic product (GDP) in many countries [5]. This financial impact highlights the urgent need for industries to invest in more effective strategies to prevent occupational diseases and reduce workplace accidents.

Recent data emphasizes the ongoing global challenge of respiratory illnesses linked to hazardous workplace exposures. The Global Burden of Disease report indicates that over 125,000 deaths have been attributed to CWP, silicosis, and asbestosis [6]. While a gradual decline in the global prevalence of pneumoconiosis has been observed since 2015, the number of workers suffering from these debilitating conditions remains significant. Mortality rates among workers afflicted with pneumoconiosis have remained alarmingly high, resulting in more than 21,000 deaths annually from 2015 onwards [7-9]. These figures reflect a persistent risk for workers in industries where exposure to harmful dust particles continues to be a daily reality. Despite substantial progress in reducing exposure levels, the persistence of these diseases underscores the necessity for innovative approaches to occupational health and safety that extend beyond traditional preventive measures.

In addition to respiratory diseases, the global workforce is continually exposed to a wide array of physical, chemical, and biological hazards, leading to injuries, accidents, and other health issues. Industries such as manufacturing, construction, transportation, and storage consistently report high rates of work-related accidents, many resulting in significant injury or death [10]. According to the International Labour Organization (ILO), approximately 2.3 million workers lose their lives each year due to work-related accidents or illnesses, translating to more than 6,000 fatalities each day. Furthermore, the ILO estimates that around 340 million occupational accidents and 160 million cases of occupational illnesses occur annually, illustrating the scale of the problem [11]. These statistics underscore the urgent need for implementing cutting-edge solutions to address both the prevention and management of workplace hazards on a global scale.

The rapid advancement of technology, particularly in the field of artificial intelligence (AI), presents new opportunities for transforming OHS practices. AI-driven technologies have the potential to revolutionize traditional approaches to workplace safety, enabling more proactive and preventive measures through real-time data monitoring, predictive analytics, and enhanced risk management tools. AI's ability to process vast amounts of data, detect patterns, and predict potential hazards offers significant opportunities to reduce the frequency and severity of workplace accidents and occupational diseases. By integrating AI technologies into existing safety protocols, industries can transition from reactive measures that address accidents and illnesses post-incident to a more proactive and preventive framework aimed at identifying and mitigating risks before they result in harm.

This review aims to encapsulate the advancements made in the integration of AI into OHS, focusing on the potential of these technologies to reshape workplace safety. AI-driven innovations, such as predictive maintenance systems, wearable safety devices, and machine learning algorithms capable of detecting early signs of occupational diseases, represent a new frontier in occupational health. These technologies not only enhance the ability to prevent accidents but also foster a culture of continuous improvement in workplace safety. By providing insights into the latest developments in AI applications within OHS, this review seeks to highlight how these technologies are contributing to safer, healthier, and more sustainable working environments.

Research Questions

(a) What specific advancements in AI are most effective in improving occupational health and safety practices?

(b) How can AI-driven technologies be integrated into existing OHS frameworks to enhance safety?

(c) What are the potential challenges and limitations of implementing AI solutions in the workplace?

(d) How can industries ensure the sustainable use of AI in OHS to maximize employee safety and health outcomes?

METHODS

This study was conducted to perform a systematic review and meta-analysis of advancements in artificial intelligence (AI) applications in occupational health and safety (OHS) from 1974 to the present. In preparing the systematic review and meta-analysis, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) directive was adhered to [12]. Throughout the study, literature review, article selection, data extraction, and quality evaluation of the included articles were independently performed by two researchers to minimize bias. In cases of disagreement on any aspect, the researchers convened to reach a consensus. There were no deviations from the protocol during the study, which was concluded in accordance with the protocol registered in the PROSPERO database.

Eligibility Criteria

The following criteria (PICOS) were utilized for selecting studies included in this review:

•**Participant (P):** Workers in various industries exposed to occupational hazards.

•**Intervention (I):** Applications of artificial intelligence in occupational health and safety.

•**Comparison (C):** Traditional methods of monitoring and managing occupational health and safety without AI applications.

•**Results (O):** Outcomes related to occupational disease prediction, diagnosis, prevention, and improvements in workplace safety.

•**Study Design (S):** Studies published in English and Turkish from 1974 to 2023, focusing on AI applications in OHS.

Studies focusing on non-AI interventions, articles lacking validity in measurement tools, and traditional systematic reviews were excluded. Additionally, non-original research, qualitative studies, unpublished theses, and descriptive studies were also part of the exclusion criteria.

Search Strategy

The literature review for this systematic review was conducted between 1974 and March 2024 using several electronic databases, including Embase, PubMed, and Google Scholar. Searches were tailored to identify studies relevant to AI applications in OHS. The keywords utilized were: "Artificial Intelligence," "Occupational Health and Safety," "Predictive Modeling," "Machine Learning," and "Deep Learning." The search strategy was adapted to suit the characteristics of each database. Furthermore, references from relevant articles and previous systematic reviews were scrutinized to discover additional studies.

Selection of Studies and Data Extraction

After removing duplicate articles from different databases, researcher conducted a comprehensive literature review, article selection, data extraction, and quality evaluation to control for bias during the study. The two independent reviewers initially assessed titles and abstracts to determine which studies met the inclusion and exclusion criteria. Studies that met the criteria or could not be clearly identified were reviewed in full text. When a consensus could not be achieved, the researchers collaboratively discussed the study's inclusion. A data extraction tool developed by the researchers was employed to gather pertinent research data, including study location, publication year, research design, sample size, and AI application specifics (Table 1).

Statistical Analysis

Meta-analysis was executed using Review Manager 5.4 (The Nordic Cochrane Center, Copenhagen, Denmark) for data analysis. The heterogeneity among studies was assessed using Cochran's Q test and Higgins' I^2 statistic, with I^2 values greater than 50% indicating significant heterogeneity. Random-effect results were utilized when I^2 exceeded 50%, while fixed-effect results were applied when it was lower. Odds ratios (OR) for categorical variables, mean differences (MD), and standardized mean differences (SMD) for continuous variables were calculated, along with corresponding 95% confidence intervals (CIs). A two-tailed P-value of less than 0.05 was regarded as statistically significant.

RESULTS

Through electronic database research and manual search, a total of 1,452 articles were identified from various databases (Embase, PubMed, Google Scholar), along with 134 from other sources, including conference proceedings and institutional reports. After removing duplicate records (n=75) and ineligible records marked by automation tools (n=1,126) not related to artificial intelligence or occupational health and safety (OHS), and non-English publications (n=20), a total of 365 records were screened.

Subsequently, 312 records were excluded based on title and abstract review. A total of 53 reports were sought for retrieval, of which 7 reports were not retrieved. The remaining 46 reports were assessed for eligibility. Out of these, 25 reports were included in the final analysis (Fig. 1).

Study Characteristics

The characteristics of the studies included in this systematic review and meta-analysis are summarized in Table 1. This analysis encompassed 25 studies conducted across various countries, including Turkey, Iran, the United States, Australia, and others, focusing on the application of artificial intelligence in the diagnosis and management of occupational diseases. All studies presented in this systematic review utilized diverse methodologies, predominantly employing retrospective analyses, randomized controlled trials

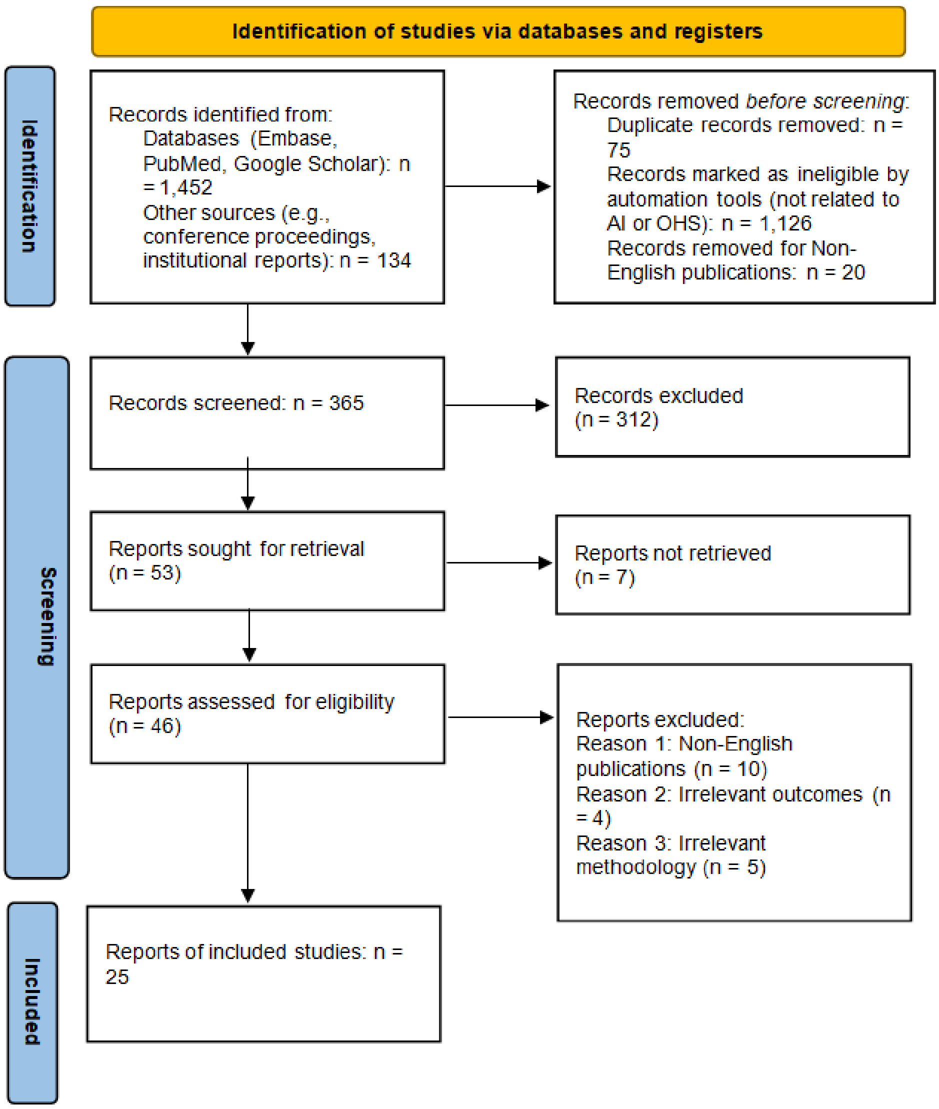

Fig. 1. PRISMA flow diagram.

Table 1. Study characteristics

Study no.	Authors & Year	Title	Methodology overview	Key findings
1	Kruger *et al.* (1974)	Computer diagnosis of pneumoconiosis	Early algorithmic approach to diagnosis	Discusses early developments in AI for pneumoconiosis diagnosis.
2	Lozano *et al.* (2012)	Global and regional mortality analysis	Systematic mortality analysis	Explores mortality rates associated with various occupational diseases.
3	Haykin (2009)	Neural Networks and Learning Machines	Theoretical overview	Explores foundational concepts in neural networks relevant to medical imaging applications.
4	Takala *et al.* (2023)	Global-, regional- and country-level estimates of work-related diseases	Epidemiological study	Presents the global burden of work-related diseases, emphasizing occupational health.
5	Matyga *et al.* (2023)	Occupational lung diseases: spectrum of common imaging manifestations	Imaging analysis of occupational lung diseases	Comprehensive review of imaging findings in various occupational lung diseases.
6	Vlahovich & Sood (2021)	A 2019 update on occupational lung diseases	Review of recent literature	Highlights advancements in the understanding and management of occupational lung diseases.
7	Qi *et al.* (2021)	Pneumoconiosis: current status and future prospects	Review of epidemiology and advancements in diagnosis	Highlights the need for improved diagnostic methods in pneumoconiosis.
8	Yates *et al.* (2021)	Dust diseases in modern Australia	Policy review and recommendations	Discusses the resurgence of dust diseases and the importance of respiratory surveillance.
9	Cellina *et al.* (2022)	Artificial intelligence in lung cancer imaging	AI applications in imaging	Explores the integration of AI in lung cancer imaging and its implications for diagnosis.
10	Choe *et al.* (2022)	Artificial intelligence in lung imaging	Overview of AI in medical imaging	Discusses the evolving role of AI in lung imaging and its impact on diagnostics.
11	Blackley *et al.* (2018)	Continued increase in prevalence of coal workers' pneumoconiosis	Epidemiological study	Reports on the increasing prevalence of pneumoconiosis among coal workers in the U.S.
12	Li *et al.* (2022)	The burden of pneumoconiosis in China	Burden analysis	Provides a comprehensive overview of the pneumoconiosis burden in China.
13	Çallı *et al.* (2021)	Deep learning for chest X-ray analysis	AI-based imaging analysis	Reviews the applications of deep learning in the analysis of chest X-rays for lung disease diagnosis.
14	Rajpurkar & Lungren (2023)	The current and future state of AI in medical image interpretation	AI applications in radiology	Evaluates the current advancements and future prospects of AI in medical imaging interpretation.
15	Litjens *et al.* (2017)	A survey on deep learning in medical image analysis	Systematic review	Provides an overview of deep learning techniques in medical image analysis.
16	Okumura *et al.* (2014)	Development of CAD based on ANN analysis of pneumoconiosis in chest radiographs	Neural network application	Examines the application of neural networks in pneumoconiosis diagnosis and detection accuracy.
17	Okumura *et al.* (2017)	Computerized classification of pneumoconiosis on digital chest radiography	AI-based deep learning model	Demonstrates the potential of AI in the early identification of pneumoconiosis stages.
18	Wang *et al.* (2023)	Automated identification of the preclinical stage of coal workers' pneumoconiosis	AI-based deep learning model	Demonstrates the potential of AI in the early identification of pneumoconiosis stages.
19	Xiaohua *et al.* (2020)	Potential of deep learning in assessing pneumoconiosis depicted on digital chest radiography	Deep learning application	Explores deep learning's effectiveness in pneumoconiosis assessment using digital radiography.
20	Zheng *et al.* (2019)	An improved CNN-based pneumoconiosis diagnosis method on X-ray chest film	CNN-based imaging analysis	Introduces an improved convolutional neural network approach for pneumoconiosis diagnosis.
21	Huang *et al.* (2022)	Transformer-based factorized encoder for classification of pneumoconiosis on 3D CT images	Transformer model application	Demonstrates the effectiveness of transformer models in classifying pneumoconiosis using 3D CT images.
22	Devnath *et al.* (2022)	Computer-aided diagnosis of coal workers' pneumoconiosis in chest X-ray radiographs using machine learning	Machine learning analysis	Provides insights into automated detection methodologies for pneumoconiosis.
23	Devnath *et al.* (2021)	Automated detection of pneumoconiosis with multilevel deep features learned from chest X-ray radiographs	Deep learning methodology	Focuses on the application of advanced deep learning techniques in pneumoconiosis detection.
24	Devnath *et al.* (2020)	Performance comparison of deep learning models for black lung detection on chest X-ray radiographs	Comparative analysis of deep learning models	Evaluates and compares various deep learning models for detecting black lung disease.
25	Arzhaeva *et al.* (2019)	Development of Automated Diagnostic Tools for Pneumoconiosis Detection from Chest X-Ray Radiographs	AI tool development	Discusses the automation of pneumoconiosis detection using advanced diagnostic tools.

(RCTs), and systematic reviews.

The design of the studies varied, with many employing machine learning algorithms for diagnostic purposes in chest imaging, such as X-rays and CT scans. Specific attention was given to the use of deep learning techniques and their effectiveness in identifying conditions such as pneumoconiosis and lung cancer. Most studies incorporated large sample sizes, enabling robust statistical analyses.

In terms of outcomes, the studies reported various metrics related to diagnostic accuracy, including sensitivity, specificity, and area under the curve (AUC) values. Many studies also highlighted the reduction in diagnostic time and improved accuracy in comparison to traditional methods.

The included studies were identified through comprehensive database searches, ensuring a wide-ranging collection of literature relevant to the intersection of AI and occupational health.

Primary Outcomes

AI and Occupational Disease Prevention

The accurate diagnosis of occupational diseases has long been a complex challenge due to the latency periods associated with many conditions. Diseases such as pneumoconiosis, silicosis, asbestosis, lung cancer, and chronic obstructive pulmonary disease (COPD) often develop over extended periods, complicating both early detection and overall management [12, 13]. Recent advancements in AI, particularly in the field of deep learning (DL), have demonstrated significant potential in revolutionizing lung disease diagnosis. AI algorithms, particularly those utilizing deep learning techniques, have shown remarkable proficiency in processing lung images, such as chest X-rays (CXRs), computed tomography (CT) scans, and magnetic resonance imaging (MRI) scans [14]. By accurately detecting and diagnosing lung conditions based on these imaging techniques, AI models provide enhanced decision-making support for healthcare professionals.

For instance, CXRs are routinely performed for workers being assessed for pneumoconiosis, a significant occupational health concern in industries where dust exposure is common. The global burden of this disease remains high, particularly in lowand middle-income countries, where industrial regulations may be less stringent [15]. The diagnosis of CWP, silicosis, or asbestosis involves complex decision-making processes that are heavily reliant on the interpretation of imaging data. Radiologists often face significant challenges in analyzing these images with consistent precision. AI-driven models, however, can analyze this imaging data with unparalleled accuracy, reducing the potential for human error and enhancing diagnostic precision [16].

Advanced AI techniques offer additional benefits by incorporating data augmentation, noise mitigation, and synthetic data generation. These techniques enable the generation of synthetic lung images that closely resemble real patient data, allowing AI models to predict future disease progression with greater accuracy. This predictive capability is especially valuable in industries where workers are continuously exposed to hazardous substances, as it allows for early intervention and the implementation of safety measures to mitigate exposure. AI's role in improving the assessment of pulmonary diseases is increasingly recognized, with several commercial AI algorithms for chest imaging already approved for use in over 20 countries [17, 18].

Historical AI Developments in Occupational Health

The application of AI in occupational disease prevention can be traced back several decades. Early algorithm-based approaches, such as those developed by Kruger *et al.*, employed hybrid optical-digital methods for medical decision-making, utilizing optical Fourier transformation techniques for occupational disease screening [19]. These early models were instrumental in identifying occupational health risks and were pivotal in compensation-related decisions for workers affected by such diseases. Classical methods of textural feature extraction, including wavelet analysis, density distribution, histograms, and co-occurrence matrices, were applied to evaluate critical features such as entropy, correlation, homogeneity, variance, and skewness. These methods provided insights into tissue composition and disease characterization through the analysis of X-ray images.

Over time, these traditional approaches were augmented by more sophisticated AI techniques. For example, multilayer perceptron (MLP) and support vector machine (SVM)-based algorithms provided the foundation for more advanced image analysis methods. As AI technologies progressed, the introduction of convolutional neural networks (CNNs) and deep learning algorithms significantly improved the precision of CXR image analysis [19, 20, 21]. These advancements enabled AI systems to classify abnormalities, identify nodules or masses, and detect disease patterns with far greater accuracy than previously possible.

Emerging AI Applications in Occupational Health

Building upon these historical foundations, AI has been successfully integrated into various aspects of OHS, particularly in improving diagnostic accuracy for occupational lung diseases. The development and application of AI algorithms in this field continue to evolve, offering promising solutions for enhancing workplace safety and reducing the incidence of occupational diseases. The following sections provide an in-depth exploration of AI's role in improving diagnostic precision, enhancing workplace monitoring, and supporting decision-making processes in the context of OHS.

Background Noise Removal Using Neural Networks in CXRs

The diagnosis of occupational lung diseases, according to the International Labour Organization (ILO), relies heavily on two key evaluation criteria: the number and area density classification of abnormalities, and the size of the abnormalities within the region of interest (ROI) of a postero-anterior chest radiograph [23]. This process, while essential, faces substantial challenges due to the presence of intricate background noise in chest radiographs. This noise is primarily caused by overlapping normal anatomical structures, such as ribs and blood vessels, which can obscure the visibility of smaller abnormalities. These structures introduce complexity into the texture analysis of CXRs, requiring the analysis techniques to exhibit a degree of insensitivity to the background in order to effectively identify abnormalities.

While early methods of background trend correction focused on removing small regions of interest (ROIs) from the image, significant progress has been made with the advent of neural network-based approaches [24]. One such advancement was demonstrated by Kondo and Kouda, who utilized a backpropagation neural network (NN) with three layers to enhance the detection of small rounded opacities in CXRs. This neural network approach effectively filtered out the rib and vessel shadows, which had previously posed a significant challenge for radiologists interpreting CXRs. By generating a suitable bi-level ROI image, the NN application was able to improve the accuracy of disease detection, particularly in cases of pneumoconiosis [25].

The proposed method by Kondo and Kouda outperformed conventional techniques by implementing a “moving normalization” process to reduce background noise. This innovative algorithm calculated the number density and area density of rounded opacities, which were then classified by comparing them to standardized ILO X-ray images. The results indicated that this approach produced more reliable outcomes than traditional methods, particularly in terms of diagnosing pneumoconiosis and similar occupational lung diseases [26]. The ability to quantify abnormalities in CXRs is crucial for decisions regarding job relocation and compensation for work-related health conditions, especially for workers exposed to hazardous dusts in industries such as mining and construction [27].

Neural Network-Based Deep Learning Applications in Non-Texture Analysis

While neural network (NN) techniques have evolved significantly over the years, their application in non-texture analysis has brought about substantial improvements in the speed and accuracy of occupational disease diagnosis. Unlike traditional manual feature extraction methods for texture analysis, deep learning (DL) algorithms have automated many aspects of disease detection, segmentation, and localization in chest radiographs. This automation has revolutionized the analysis of CXRs, leading to more efficient and precise diagnostic processes, particularly in the classification and interpretation of pneumoconiosis [28].

One such development in the field is the detection scheme for pneumoconiosis developed by Okumura *et al*., which employed a combination of rule-based methods and artificial neural network (ANN) analysis [29]. This hybrid approach incorporated three image enhancement techniques-window function, top-hat transformation, and gray-level co-occurrence matrix analysis-to differentiate between normal and abnormal regions of interest (ROIs) in CXRs. When applied to chest radiographs representing both severe and low-grade pneumoconiosis, the method achieved significant classification performance, with areas under the curve (AUC) of 0.93±0.02 for severe cases and 0.72±0.03 for low-grade cases [28]. These results underscore the efficacy of using DL methods for automated disease detection, particularly in identifying subtle abnormalities that might be overlooked by human interpretation.

Further advancements in NN-based DL applications have also been reported, particularly in terms of improving diagnostic accuracy for different stages of pneumoconiosis. Okumura *et al*. extended their work by using a three-stage ANN to achieve AUC values of 0.89 ± 0.09 for low-grade pneumoconiosis and 0.84±0.12 for severe cases [29]. These results indicate that while ANN algorithms have made significant strides in automating the diagnostic process, challenges remain in their ability to fully capture the complexity of pneumoconiosis CXRs. Neural networks, particularly in the context of medical imaging, can struggle to learn complex representations of diseases, which limits their applicability in more intricate diagnostic tasks.

Nevertheless, despite these limitations, the ongoing development of NN-based DL algorithms continues to improve the efficiency and effectiveness of occupational lung disease diagnosis. As research in this area progresses, further refinements in algorithmic structure and training methods are expected to enhance the performance of these systems, potentially leading to more widespread adoption in clinical settings. By addressing the current shortcomings of neural networks in handling complex tasks, future innovations hold the promise of improving diagnostic outcomes for workers at risk of occupational lung diseases, ultimately contributing to better occupational health and safety standards.

Convolutional Neural Networks (CNNs) and Their Application in Medical Imaging

The era of artificial intelligence (AI) has ushered in remarkable advancements in medical imaging, particularly with the integration of deep learning (DL) techniques. Among these, convolutional neural networks (CNNs) have led to a paradigm shift in medical image processing by providing unparalleled accuracy in the analysis and classification of complex medical images. CNNs such as LeNet, AlexNet, GoogLeNet, and ResNet represent some of the most influential architectures that have driven progress in this field. LeNet, one of the earliest CNN models, was pivotal in laying the foundation for digital classification through its application of a 32 × 32 image size [30]. However, its performance reached a plateau due to the model's inherent limitations, which were later addressed by more sophisticated architectures.

In 2012, AlexNet made significant strides by achieving exceptional results in the ImageNet competition, which opened new possibilities for CNN applications across a variety of domains, including medical imaging [31, 32]. Two years later, GoogLeNet was introduced, providing further improvements in network design, particularly in terms of computational efficiency and accuracy [33]. The evolution continued with the introduction of ResNet in 2015, which represented a major advancement in network depth and convergence speed by addressing the vanishing gradient problem that had previously hindered deep networks [34]. These developments laid the groundwork for adapting CNN architectures to specific challenges in medical image analysis, including chest X-ray (CXR) classification for occupational lung diseases.

Adapting CNNs for CXR Analysis and Pneumoconiosis Diagnosis

In recent years, researchers have increasingly adapted CNN architectures to address the unique challenges associated with classifying CXRs, particularly in the diagnosis of pneumoconiosis. One key innovation in this area has been the use of transfer learning, where pretrained CNN models are fine-tuned for specific tasks such as CXR analysis. This approach mitigates the limitations associated with the scarcity of labeled medical data, as collecting large-scale, accurately annotated medical images is often both time-consuming and expensive [35, 36, 37]. Transfer learning allows models trained on large-scale datasets, such as ImageNet, to be adapted to the more specific task of CXR classification, yielding improved performance in detecting and diagnosing occupational lung diseases.

Several studies have explored the application of CNNs to pneumoconiosis diagnosis, with researchers such as Devnath *et al*. [38, 39, 40], Arzhaeva *et al*. [41], and Zhang *et al*. [42] making significant contributions to the field. Most of these studies employed CNN models pretrained on the ImageNet dataset. For instance, Zheng *et al*. [47] utilized a variety of CNN architectures, including LeNet, AlexNet, and GoogLeNet (Inception-v1 and Inception-v2), to optimize the detection of pneumoconiosis. The optimized GoogLeNet-CF (Inception-CF) model achieved an impressive accuracy of approximately 96.88% when trained on 1,600 images, outperforming other models such as GoogLeNet (94.2%), Inception-v2 (90.70%), AlexNet (87.90%), and LeNet (71.6%) [47]. This high level of accuracy demonstrates the efficacy of advanced CNN models in identifying occupational lung diseases, particularly when larger datasets are available for training.

In another study, a deep CNN model was applied to one of the largest CXR datasets, consisting of 33,493 images. The model achieved an accuracy rate of 92%, with a sensitivity of 99%, significantly reducing the likelihood of missed diagnoses [46]. This exceptional sensitivity makes CNN models ideal tools for screening pneumoconiosis in occupational health assessments, particularly in regions such as China, where large populations are exposed to hazardous dust in industrial settings [46]. Another notable application of CNNs was conducted by Wang *et al*., who employed the Inception-V3 (GoogLeNet) architecture to detect pneumoconiosis, achieving an area under the curve (AUC) of 87.80, indicating the strong potential of deep learning methods in this domain [43].

Deep Learning and Transfer Learning for Enhanced CXR Analysis

Several investigations by Devnath *et al*. [48] have further examined the performance of CNN classifiers, both with and without transfer learning, in classifying black lung disease. The models evaluated in these studies included VGG16, VGG19, InceptionV3, Xception, ResNet50, DenseNet121, and CheXNet [40, 49]. Due to the limitations in data size, with only 71 Posterior-Anterior (PA) CXR images available, the researchers employed advanced techniques such as Cycle-Consistent Adversarial Networks (CycleGAN) and Keras Image Data Generator to create additional synthetic and augmented radiographs, including ILO standard radiographs. The accuracy of these models varied, with InceptionV3 achieving the highest performance (88%), followed by CheXNet, Xception, ResNet, DenseNet, VGG16, and VGG19 [40].

In another investigation, Devnath *et al*. [39] applied a pair of CNN models to extract multidimensional features from pneumoconiosis CXR images. These models included an unpretrained DenseNet and a pretrained CheXNet architecture. The extracted features were then input into a traditional machine learning classifier, specifically a support vector machine (SVM). The hybrid CheXNet approach proved highly effective, achieving an accuracy of 92.68% in the automated identification of pneumoconiosis, surpassing alternative methods based on both traditional machine learning and deep learning [39]. This hybrid methodology highlights the potential of combining CNN-based feature extraction with conventional classifiers to enhance diagnostic accuracy in challenging medical imaging tasks.

Preclinical Stage Classification of Pneumoconiosis Using Deep Learning Methods

Once pneumoconiosis is diagnosed, it often means the disease has reached an advanced stage, making treatment significantly more difficult. This challenge highlights the need for early detection, ideally during the preclinical stage, to manage the disease more effectively. Early identification would not only help reduce the incidence but also mitigate the severity of the disease among workers who are exposed to hazardous environments, particularly in industries such as mining and construction [2]. Recognizing the importance of early detection, AI-based research has focused on developing models to identify pneumoconiosis during its preclinical stage.

A notable advancement in this area is the work of Wang et al., who proposed a novel three-stage cascaded learning model for preclinical diagnosis. The initial phase of this model involved training a YOLOv2 network to detect lung regions within digital chest radiography (DR) images [44]. In the second phase, six distinct convolutional neural network (CNN) models were trained to recognize the preclinical phase of coal workers' pneumoconiosis (CWP). In the final phase, the authors implemented a hybrid ensemble learning (EL) model, utilizing a soft voting mechanism to combine the outputs of the six CNN models.

The dataset used for training and validation comprised 1,447 digital radiographs, sourced from workers including drillers, coal-getters, auxiliary workers, and other coal industry personnel. The six CNN models employed in the study included Inception-V3, ShuffleNet, Xception, DenseNet, ResNet101, and MobileNet, each contributing to the overall classification process. The cascade model demonstrated an impressive area under the curve (AUC) of 93.1%, with an accuracy of 84.7%, indicating its potential as a powerful tool for preclinical screening of coal workers [44]. This promising approach marks a significant step forward in the use of deep learning methods for the early identification of occupational lung diseases, specifically CWP, in at-risk populations.

Vision Transformer-Based Pneumoconiosis Classification Using CT Images

Traditionally, neural network (NN) architectures such as CNNs have been widely applied to various image classification tasks, including the detection and classification of pneumoconiosis based on 2D chest X-rays (CXR). However, recent advancements in machine learning (ML) have introduced the Transformer architecture, initially developed for natural language processing (NLP) tasks. This architecture has now been adapted for computer vision tasks, leading to the development of Vision Transformer (ViT), which has demonstrated competitive performance compared to conventional CNNs across several image classification benchmarks [51, 52].

While CNN-based methods have been effective in categorizing abnormalities in 2D CXR images [28, 29, 39, 49, 53, 54, 55], there is limited literature on the use of 3D computed tomography (CT) images for pneumoconiosis classification. Given the higher resolution and enhanced diagnostic capabilities of CT images compared to CXRs, CT has emerged as a reliable method for diagnosing lung disorders, offering greater sensitivity and detailed diagnostic insights. In this context, a recent study conducted by Huang *et al*. at the largest occupational disease authentication center in western China applied a transformer-based factorized encoder (TBFE) model to analyze 3D CT images of pneumoconiosis [45].

The TBFE model demonstrated an enhanced ability to classify the severity of pneumoconiosis by analyzing both intra-slice and inter-slice information, addressing the unique challenges posed by 3D medical imaging. In comparison with other popular 3D CNN models, such as CheXNet, COVID-Net, and various ResNet and ResNeXt versions, TBFE performed significantly better. The model achieved an impressive accuracy of 97.06% and an F1 score of 93.33%, demonstrating its superior precision and recall compared to alternative methods. Moreover, TBFE proved particularly effective in predicting the initial stage (stage 0) of pneumoconiosis, an area where conventional 3D CNN networks had previously struggled.

These performance indicators highlight the potential of transformer-based models in medical imaging, particularly for the early diagnosis of pneumoconiosis. The TBFE's ability to accurately classify different stages of pneumoconiosis based on 3D CT images suggests that this model could play a crucial role in improving occupational health assessments and preventive care for workers in high-risk industries. The use of TBFE, with its high precision, may assist in more effective screening and early intervention strategies, thus reducing the burden of this disease among exposed populations.

AI and Occupational Safety Enhancements

Artificial intelligence (AI) has emerged as a transformative force across numerous industries, significantly altering the ways in which tasks are performed, managed, and evaluated. By leveraging advanced computational techniques, AI is capable of analyzing vast quantities of data and facilitating decision-making pro

cesses that directly impact labor dynamics and workplace operations. Key AI technologies, such as machine learning (ML), deep learning (DL), natural language processing (NLP), and rule-based expert systems (RBES), have proven instrumental in enhancing efficiency and accuracy in various occupational settings. These technologies have also become pivotal in occupational health and safety, where they enable the examination of both structured and unstructured data, leading to better risk management and safety solutions.

AI has found applications in several critical areas of occupational safety. For instance, in industrial environments, AI-driven systems are used to coordinate machinery, optimize industrial processes, and manage the workforce from a human resources (HR) perspective. These applications include workforce scheduling, performance monitoring, and assessing the risks associated with various job roles. AI technologies have also been applied in customer risk assessment, benefits analysis, and evaluating staff safety, providing employers with comprehensive insights into workplace dynamics [56]. Through these capabilities, AI can help employers create safer, more efficient work environments by proactively identifying potential risks and hazards.

To further promote workforce safety, employers can implement several strategies as recommended by the US National Institute for Occupational Safety and Health (NIOSH). These strategies include offering extensive training on job hazards, developing comprehensive safety programs, and providing personal protective equipment (PPE) to mitigate workplace risks. However, despite the availability of these preventive measures, human error continues to be a major contributor to workplace accidents. Human limitations in processing vast amounts of data or recognizing subtle patterns of risk can leave organizations vulnerable to unexpected incidents.

This is where AI's capabilities become particularly valuable. Due to its ability to rapidly process and analyze large datasets, AI can identify potential risks and hazards that may go unnoticed by human workers. For example, AI can detect patterns in workplace incidents, predict hazardous conditions, and recommend interventions before accidents occur. This predictive power enables a shift from reactive safety measures to a more proactive approach, significantly reducing the likelihood of accidents [57].

AI has also introduced innovative ways to assess employee performance, particularly in environments where manual evaluations may be prone to bias or human oversight. AI-powered systems can objectively evaluate employee performance based on data collected from sensors, machines, or even video footage, helping employers identify areas for improvement while simultaneously enhancing workplace safety. For instance, AI can track whether employees are adhering to safety protocols, such as wearing PPE or following proper procedures when operating heavy machinery. When deviations from safety standards are detected, the system can alert supervisors or suggest corrective actions to prevent potential injuries.

Moreover, AI technologies such as computer vision and robotics are being integrated into workplace environments to further enhance safety measures. Computer vision systems can monitor real-time activities, detecting dangerous behaviors or situations that require immediate intervention. Robotics, combined with AI, can automate hazardous tasks, reducing the exposure of workers to potentially dangerous environments. These AI-driven solutions create a safer working environment by minimizing the risks posed by human error and ensuring that safety protocols are continuously upheld.

As the role of AI continues to expand in occupational health and safety, the potential benefits become increasingly clear. AI offers a unique opportunity to shift the focus from reactive safety measures to proactive prevention, enabling organizations to identify and address risks before they escalate into incidents. By automating safety processes and enhancing human decision-making with data-driven insights, AI is poised to play a central role in shaping the future of workplace safety. As more industries adopt AI-driven safety solutions, the overall goal is to create safer, more efficient, and more sustainable workplaces.

AI-Driven Exoskeletons

The development and utilization of exoskeletons—wearable robotic suits designed to augment the mobility and strength of the limbs and joints—have emerged as a promising technology for enhancing productivity while simultaneously safeguarding the health and well-being of workers. These wearable devices are particularly beneficial in physically demanding tasks, offering additional support that can mitigate the risk of injuries. Research has shown a growing reliance on various artificial neural network (ANN) structures in modern exoskeleton technologies, which are increasingly being integrated with traditional control methods and adaptive optimizers to create more resilient hybrid systems [58, 59]. Throughout the evolution of biomechatronics and intelligent systems, ANNs have played a foundational role in enabling the development of advanced assistive technologies, including brain-machine interface-controlled prosthetics and robotic exoskeletons designed for rehabilitation purposes [60].

In occupational settings, exoskeletons serve a dual purpose: they facilitate biometric analysis and aid in rehabilitation following injuries, while also alleviating physical strain on workers. By reducing the pressure placed on the spine and other critical areas of the body, exoskeletons can improve overall physical health for employees engaged in repetitive or strenuous tasks. One of the key advantages of these devices is their ability to provide support to the lower back, which is often the part of the body most affected by heavy lifting and other physically demanding activities [61]. For example, German Bionics has developed two commercially available exoskeletons, the Cray X and the recently introduced Apogee. These devices are worn like backpacks and are equipped with electric motors that sense the user's movements, delivering up to 30 kg of additional force to the back, core, and legs when needed [62, 63]. This added support reduces the risk of musculoskeletal injuries and helps workers perform physically demanding tasks with greater ease.

In recent years, the use of powered exoskeletons has expanded beyond occupational settings into clinical environments, where they have been utilized for rehabilitation and mobility assistance. Devices such as the Indego, Exo H3, ReWalk, HAL, and Ekso GT exoskeletons, along with smart walkers like JARoW, i-Walker, and the FriWalk robotic walker, have been developed to assist individuals with mobility impairments [64-71]. These devices have proven to be valuable tools in both rehabilitation and everyday activities, enabling users to regain or maintain mobility and reduce dependence on caregivers.

Occupational Exoskeletons and Workplace Safety

In the context of occupational health and safety, exoskeletons have been strategically designed to minimize the risk of injuries, particularly to the back and shoulders. These devices are employed in work environments where conventional ergonomic solutions may not be sufficient to protect workers from injury. By providing mechanical support during tasks that require heavy lifting, repetitive movements, or awkward postures, exoskeletons help alleviate muscle strain and fatigue, ultimately enhancing workplace safety. Major companies such as Toyota, Ford, and Boeing have been at the forefront of integrating exoskeleton technologies within their workforce. Over the past decade, these companies have reported significant reductions in injury rates, with some groups experiencing an 83% decrease in injuries after adopting exoskeleton technology [72].

The benefits of exoskeletons extend beyond injury prevention. Workers who utilize exoskeletons often report lower levels of discomfort, reduced fatigue, and fewer physical complaints. These devices also contribute to decreased workers' compensation costs, as the reduction in workplace injuries translates into fewer claims and lower healthcare expenses. Studies have shown that exoskeletons can effectively reduce the physical demands placed on workers across various industries, including logistics, construction, manufacturing, healthcare, and even the military. In these sectors, workers are often required to perform physically demanding tasks for extended periods, and the use of exoskeletons has been shown to alleviate the strain associated with such tasks [73].

Furthermore, AI-driven exoskeletons are increasingly being equipped with intelligent systems that enable real-time adjustments based on the user's movements and the task being performed. These systems use machine learning algorithms to continuously analyze data from the exoskeleton's sensors, optimizing the level of assistance provided and ensuring that the device operates efficiently and safely. As AI technology continues to advance, future exoskeletons are expected to become even more responsive and adaptive, further enhancing their utility in both occupational and clinical settings.

The adoption of exoskeleton technology in the workplace represents a significant step forward in the effort to protect workers from injury while improving productivity and efficiency. By reducing the physical toll of demanding tasks, these devices not only enhance worker safety but also contribute to overall job satisfaction and well-being. As more industries recognize the value of exoskeletons, their integration into everyday work practices is likely to expand, paving the way for safer and more sustainable working environments.

Workplace Safety and AI-Enabled PPE

In today's rapidly evolving technological landscape, ensuring workplace safety requires the modernization of conventional tools and procedures. With the increasing complexity of industrial environments and the persistent risk of accidents, there is a growing need to integrate advanced technologies, such as artificial intelligence (AI), into safety protocols. Recent studies have explored the role of AI in the manufacturing sector, highlighting its potential to enhance safety and efficiency across industries [74-77]. This integration not only improves operational processes but also maximizes the protection and security of workers. The advent of smart personal protective equipment (PPE) and wearable technologies has enabled the real-time collection of data regarding both the workforce and their surroundings. This data-driven approach has the potential to significantly reduce the frequency of workplace accidents and occupational health issues, thereby improving overall safety conditions [78].

Advancements in AI-Enabled Smart PPE

Modern smart PPE technologies are equipped with advanced sensors that track critical health indicators and assess environmental conditions in industrial settings. These devices are part of a broader trend toward the incorporation of wearables in the workplace, providing valuable insights into worker safety and the surrounding environment. By leveraging AI techniques such as neural networks (NNs), fuzzy logic, Bayesian networks, decision trees, and hybrid inference methods, smart PPE can offer proactive safety solutions [79]. Unlike traditional safety systems, which typically follow a reactive "action-reaction" approach by responding only when a threshold is exceeded, AI-enabled systems incorporate learning mechanisms that allow them to anticipate and prevent accidents based on contextual factors. These systems are designed to continuously learn from previous situations, making them adaptable to new or unforeseen risks.

Incorporating AI technologies such as neural networks, case-based reasoning (CBR) systems, deep learning (DL), or hybrid neuro-symbolic algorithms allows smart PPE to assess whether certain conditions pose a safety risk. These AI-driven systems enhance the flexibility and responsiveness of safety protocols, ensuring that they can adapt to the dynamic nature of modern industrial environments [80-82]. As a result, AI-enabled smart PPE is capable of identifying risks in real-time and taking preventive measures to safeguard workers.

Smart Boots

One example of AI-enabled smart PPE is the development of smart boots, which are equipped with sensors and AI algorithms designed to continuously monitor the wearer's environment. These boots are capable of detecting hazardous conditions, such as slippery surfaces or obstacles, and providing real-time alerts or interventions to prevent accidents. By offering a proactive approach to risk mitigation, smart boots not only enhance worker safety but also demonstrate the transformative potential of AI in occupational safety standards.

Smart boots are designed with a range of advanced functionalities, including fall detection, geofencing, nocturnal flashlight capabilities, local data storage and analysis, bidirectional communication systems for alerts, and tactile feedback mechanisms. These features provide comprehensive safety support, enabling workers to operate in potentially hazardous environments with greater confidence. Companies have developed hardware modules that can be integrated with existing safety boots, transforming them into intelligent devices capable of significantly reducing the risk of workplace injuries [83]. This technology has proven particularly useful in industries where workers are regularly exposed to challenging environmental conditions, such as construction, logistics, and manufacturing.

Smart Helmets

Another key innovation in AI-enabled PPE is the smart helmet. Smart helmets are equipped with a variety of sensors, including global positioning systems (GPS), radio frequency identification (RFID), ultra-wideband (UWB) sensors, and around-view monitors (AVMs). These sensors work together to track the location, activities, and health of workers, as well as monitor the surrounding environment. A unique feature of smart helmets is their ability to detect air quality, which is crucial for alerting workers and safety officers to the presence of hazardous gases and pollutants. This makes smart helmets an invaluable tool in industries where air quality is a critical concern, such as mining, chemical manufacturing, and oil and gas production.

Several smart helmets are currently available on the market, each offering advanced safety features. For example, the Guardhat Communicator, HMT1, XR10 with HoloLens 2, and the Smart Helmet by Excellent Web World all provide real-time monitoring and data transmission capabilities. The Smart Helmet by Excellent Web World stands out for its ability to gather and transmit job site data, along with personal information, to ensure a safer work environment. This feature is particularly useful for workers in confined spaces, tunnels, or areas with gas lines, where the risk of exposure to dangerous gases or structural hazards is heightened [84].

The integration of AI into workplace safety equipment, such as smart boots and helmets, represents a significant advancement in occupational health and safety. These AI-enabled devices offer real-time monitoring and proactive risk mitigation, allowing employers to take preventative measures before accidents occur. By incorporating AI technologies into PPE, companies can create safer work environments that not only protect workers but also improve operational efficiency. As industries continue to adopt smart PPE solutions, the future of workplace safety will be shaped by AI's ability to anticipate and address potential risks, ultimately leading to healthier and more secure working conditions.

Workplace Safety Through AI-Based Robots

The transformative impact of AI-based robotics on workplace safety is undeniable, as these technologies significantly reduce the risk of injuries and fatalities by minimizing workers' exposure to dangerous machinery and hazardous environments [85-87]. Recent studies, such as the one conducted by Gihleb *et al*. in 2022, have provided compelling evidence of this benefit. Their research, based on establishment-level data on injury rates, found that a 1 standard deviation (SD) increase in robot exposure (equivalent to 1.34 robots per 1,000 workers) is associated with a reduction of approximately 1.2 work-related injuries per 100 full-time workers (0.15 SDs; 95% CI, 1.8-0.53) [84, 86]. These findings underscore the potential of AI-driven robots to improve workplace safety, especially in high-risk environments where workers are typically exposed to hazardous materials, extreme heights, or confined spaces.

While AI-enabled robots offer significant safety advantages, they also introduce their own set of risks. The increased deployment of autonomous systems in the workplace requires careful consideration of both the benefits and potential drawbacks. For this reason, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have become integral technologies in the field of robotics [88-90]. According to industry projections, by 2024, up to 75% of enterprises will have integrated AI into their operational workflows, reflecting the growing reliance on these technologies to enhance safety and productivity [91].

Recognizing the potential safety implications of robots in the workplace, the National Institute for Occupational Safety and Health (NIOSH) established the Center for Occupational Robotics Research (CORR) in 2017. CORR is dedicated to assessing the advantages and challenges of incorporating robots into the workforce, providing guidance on optimizing safety while maximizing the efficiency of robotic systems [92].

Autonomous Mobile Robots and Enhanced Safety

One of the most significant contributions to workplace safety comes from the use of autonomous mobile robots (AMRs). These robots, including automated guided vehicles (AGVs), are widely used in industries such as construction, healthcare, and logistics. AMRs are designed to perform tasks that pose collision risks or cause physical strain, such as heavy lifting, transporting goods, or disinfecting hospital equipment [93, 94]. For example, robots developed by a Denmark-based robotics company can carry payloads of up to 1,350 kg, handling physically demanding tasks in dynamic environments and significantly reducing the risk of injuries such as back strain or falls. AMRs are equipped with advanced multisensor safety systems that include laser scanners, 3D cameras, and proximity sensors. These sensors feed data into sophisticated planning algorithms that enable the robot to navigate its environment safely, making real-time adjustments to avoid obstacles or stop when necessary. In cases where sensor malfunction occurs, these robots are programmed with AI-driven decision-making features that allow them to continue operating safely, further enhancing their reliability [95, 96].

AI Robots in Industry: Examples of Advanced Applications

AI-based robots are being developed and deployed in a variety of industries, with different models designed for specialized tasks. These robots are not yet true AI but incorporate AI approximations to enhance their functionality. Some prominent examples of AI robots in the industry include:

•**Digit by Agility Robotics:** Digit is a humanoid bipedal robot designed to navigate complex terrains and perform tasks such as package delivery. It is capable of climbing stairs, catching itself during falls, and planning its movements to avoid obstacles. In hazardous work environments, Digit could be deployed for tasks such as emergency response and disaster recovery, minimizing the risks faced by human workers [97].

•**Atlas and Spot by Boston Dynamics:** These advanced robotic platforms are designed for search-and-rescue operations. Atlas, a humanoid robot, and Spot, a quadruped, can navigate hazardous or hard-to-reach areas to locate and assist personnel. These robots are particularly useful in handling and transporting hazardous materials, such as chemical agents or explosives, reducing the risk of fire, explosions, or other dangerous incidents in industrial environments [98].

•**HRP-5P by AIST:** Developed by Japan's Institute of Advanced Industrial Science and Technology (AIST), HRP-5P excels in heavy labor tasks, particularly in the construction industry. This robot is capable of autonomously installing gypsum boards on walls and handling large plywood panels, mitigating the hazards associated with heavy lifting and repetitive strain injuries in construction work [99].

•**Aquanaut by Houston Mechatronics:** Aquanaut is an unmanned underwater submersible designed for tasks in hazardous underwater environments. With the ability to travel over 200 kilometers underwater and manipulate objects using onboard sensors and cameras, Aquanaut minimizes the need for human divers in dangerous underwater missions, such as deep-sea exploration or oil rig maintenance [100].

•**Stuntronics by Disney:** Disney's Stuntronics robot is designed to perform acrobatic stunts for movies and theme park shows. Using sensors and autonomous pose control, the robot can execute complex maneuvers with precision, reducing the need for human stunt doubles in high-risk scenes. Studies have highlighted the dangers faced by stunt performers, and technologies like Stuntronics aim to minimize these occupational hazards [101-103].

The integration of AI-based robotics in the workplace represents a significant leap forward in improving occupational safety. These robots reduce the risk of injuries and fatalities by performing dangerous tasks traditionally carried out by human workers. However, it is important to consider the risks associated with the use of robots, as the incorporation of AI and robotics into the workforce presents new challenges. Nevertheless, the potential for AI-driven robots to enhance workplace safety is immense, and as the technology continues to evolve, we can expect further breakthroughs that will create safer, more efficient work environments.

AI Computer Vision in Monitoring and Surveillance Tools for Workplace Safety

Computer vision, a key area of artificial intelligence (AI), has shown immense potential in enhancing workplace safety through its advanced monitoring and surveillance capabilities. By utilizing AI-driven computer vision technologies, organizations can implement real-time safety monitoring, improve hazard detection, and enhance overall risk management strategies [104]. One of the notable applications of computer vision in workplace safety is the use of thermal cameras to monitor heat stress in workers. This technology enables continuous surveillance of employees' body temperatures, allowing for timely interventions such as cooling breaks or the provision of personal protective equipment (PPE) designed to mitigate heat exposure. These proactive measures can prevent heat-related illnesses and contribute to maintaining a safer work environment.

In addition to managing heat stress, AI-powered computer vision systems are widely used for general surveillance tasks, such as tracking employee movements and detecting potential hazards. For example, AI-enabled cameras can identify trip hazards, unsecured equipment, or instances of unsafe behavior, alerting supervisors in real-time to take corrective action. These systems are capable of monitoring restricted areas and can detect when an unauthorized individual enters a hazardous zone, helping to prevent accidents and ensuring compliance with safety protocols [105, 106]. By automating these surveillance tasks, AI-based computer vision reduces the likelihood of human error and provides continuous, accurate oversight of the work environment.

AI-Driven Platforms for Workplace Safety

The rapid advancement of AI and machine learning (ML) technologies has revolutionized workplace safety by introducing innovative platforms designed to manage data and analyze visual inputs in real-time. Computer vision is central to this shift, as it enables the efficient processing of video data and the detection of objects, hazards, or safety violations. Several AI-powered platforms have emerged to cater to the diverse needs of industries, offering a range of tools for data labeling, curation, object detection, and video analysis. Notable platforms in this field include Scale

AI, Supervisely, V7, Viso, Labelbox, Toloka, Superannotate, and OpenCV. OpenCV, in particular, is an open-source computer vision and ML library that has become an integral part of the AI landscape, widely used for the development and deployment of advanced surveillance and safety applications.

These platforms facilitate the development of AI-powered systems by providing a robust infrastructure for labeling large datasets, training deep learning (DL) models, and fine-tuning pretrained configurations. The growing availability of these platforms has enabled industries to quickly implement computer vision solutions tailored to their specific safety needs, reducing the time and cost associated with developing AI-driven surveillance systems. By leveraging AI platforms, organizations can streamline the process of creating intelligent surveillance systems that improve workplace safety by accurately identifying risks and alerting relevant personnel in real-time.

Deep Learning and Computer Vision in Workplace Safety

The integration of deep learning (DL) models into computer vision applications has transformed workplace safety, enabling the development of sophisticated systems capable of addressing a wide range of safety concerns. Deep learning algorithms, particularly convolutional neural networks (CNNs), have become the cornerstone of computer vision technologies, allowing for precise classification, recognition, and detection tasks in real-world environments. These advancements in DL have allowed organizations to deploy AI-based solutions for video analysis, gesture detection, and robotics, contributing to a safer and more efficient workplace.

For instance, DL models can be trained to analyze live video feeds from surveillance cameras, identifying unsafe conditions or behaviors, such as a worker not wearing the required PPE or engaging in activities that may lead to injury. Gesture detection technologies powered by DL can monitor workers' physical movements, detecting signs of fatigue, distress, or unsafe posture that could lead to accidents. Additionally, DL-enhanced robotics can autonomously navigate workspaces, performing inspections or completing tasks in hazardous environments without putting human workers at risk.

While deep learning models have significantly improved the capabilities of computer vision in workplace safety, several challenges remain. Computer vision systems must contend with complex visual environments, including varying lighting conditions, occlusions, and changes in perspective, all of which can complicate the task of accurate detection and classification. Moreover, the rapidly evolving nature of workplace hazards requires computer vision systems to continually adapt and improve through fine-tuning and retraining of DL models. Despite these challenges, CNNs and other DL architectures have proven to be powerful tools in addressing the dynamic needs of workplace safety [107].

The integration of AI-driven computer vision technologies into workplace safety protocols represents a major leap forward in improving the monitoring and management of potential risks. From thermal cameras that track heat stress to advanced surveillance systems capable of detecting trip hazards and unauthorized access to restricted areas, AI computer vision plays a pivotal role in creating safer work environments. The use of AI platforms for data management, object detection, and video analysis further enhances the ability of organizations to deploy intelligent safety systems that can proactively identify and mitigate risks.

As deep learning continues to evolve, the potential for AI-powered computer vision to transform workplace safety will only increase. The development of increasingly sophisticated models and algorithms will allow for more precise and reliable detection of hazards, improving safety outcomes across a range of industries. By embracing AI-enabled computer vision technologies, organizations can create more adaptive, efficient, and secure work environments, ultimately contributing to the well-being and safety of their employees.

AI-Based Virtual Reality for Employee Training

Virtual reality (VR) has become an increasingly valuable tool in safety training, particularly for industries where real-life experience in high-risk scenarios can be dangerous or impractical. By immersing employees in a simulated environment, VR provides a safe yet realistic platform for them to gain practical knowledge and experience, helping to build risk-preventive knowledge. This approach not only enhances worker safety but also minimizes the likelihood of workplace accidents and fatalities [108]. As a cost-effective, goal-oriented solution, VR enhances accident prevention by allowing employees to experience and respond to high-risk situations without exposure to actual hazards. The immersive nature of VR also makes it a more engaging and memorable training method compared to traditional formats like PowerPoint presentations or videos [109].

By offering a hands-on learning experience, VR simulations enable workers to practice responses to hazardous scenarios in a controlled environment. This interactive approach not only improves retention but also equips employees with the skills necessary to manage real-world risks more effectively. As a result, VR has been increasingly adopted in industries with high-risk environments, such as chemicals, construction, mining, and defense, where the reduction of workplace injuries and fatalities is critical. These industries have recognized the value of VR in delivering practical safety training at a fraction of the cost associated with traditional in-person training programs.

Applications of VR in Various Industries

Several industries have implemented VR-based training programs to improve employee safety and reduce accident rates:

•**Chemical Processing:** The "Immersive Virtual Reality Plant" provides employees with a virtual tour of hazardous environments, guiding them through potentially dangerous scenarios. This simulation prepares workers to respond effectively in real emergencies, improving their ability to handle critical situations without risking exposure to harmful substances.

•**Construction:** In construction, VR is used in conjunction with Building Information Modeling (BIM) technology to create simulations that familiarize workers with hazardous zones and safe practices on construction sites. By experiencing these scenarios in a virtual environment, workers are better prepared to avoid accidents when they encounter real-life hazards.

•**Mining:** The University of New South Wales School of Mining Engineering has incorporated VR into its training programs to educate students on emergency response protocols. By simulating mining accidents and other dangerous situations, the VR system allows students to practice appropriate responses in a safe and controlled environment, which enhances their preparedness for real-world challenges.

•**Military:** In the defense sector, VR is used to train personnel for emergency and disaster response. For example, the Naval Engineering Academy has partnered with Ethosh to create VR simulations that teach sailors how to manage emergency situations onboard ships. These immersive training sessions help ensure that personnel follow precise protocols when faced with real-world emergencies.

Industry-Wide Adoption of VR in Safety Training

The use of VR for occupational safety training has rapidly expanded, with organizations recognizing the technology's potential to significantly improve worker safety and operational efficiency. For example, AST Arbeitssicherheit & Technik has implemented VR platforms for training employees on how to safely handle earth-moving machinery [110]. Similarly, chemical and consumer goods company Henkel has collaborated with VRdirect to create a VR training experience that educates employees about health and safety risks in the workplace. By gamifying the learning process, Henkel's training program challenges employees to identify potential hazards in busy workplace scenes, making the learning experience both effective and enjoyable [111].

Large corporations such as Walmart, FedEx, and BP have also embraced VR for safety training, recognizing its potential to enhance worker engagement and retention. At Walmart, VR is used to simulate various scenarios that employees might encounter, such as managing spills or handling hazardous equipment. This enables workers to practice safety protocols in a risk-free environment. Similarly, FedEx and BP have integrated VR into their safety training programs to teach employees how to respond to emergency situations, reducing the likelihood of accidents and injuries [112].

Benefits of AI Integration in VR Training

The integration of AI into VR-based training systems further enhances the effectiveness of these programs by offering personalized learning experiences. AI-driven algorithms can analyze an employee's performance in a virtual environment, identifying areas for improvement and tailoring future training sessions to focus on specific skills. This adaptive approach ensures that each employee receives targeted training that addresses their unique needs and gaps in knowledge. AI also enables real-time feedback during VR simulations, providing employees with instant guidance on how to correct mistakes or improve their responses to hazardous situations.

Moreover, AI-powered VR training can incorporate predictive analytics to anticipate potential workplace hazards based on data collected from previous simulations. This allows employers to proactively address risks before they lead to accidents, further improving workplace safety. As AI technology continues to evolve, the combination of AI and VR will likely become a cornerstone of safety training programs across various industries, providing organizations with an innovative, efficient, and effective way to prepare employees for the challenges of their work environments.

The integration of AI-based virtual reality in employee safety training marks a significant step forward in workplace safety. By providing immersive, interactive learning experiences, VR offers employees the opportunity to practice risk prevention in a controlled, simulated environment, significantly reducing the risk of real-world accidents. As industries continue to adopt VR for safety training, and as AI technology further enhances the adaptability and personalization of these programs, the future of workplace safety looks increasingly promising. The continued evolution of AI-driven VR training solutions will undoubtedly play a pivotal role in creating safer, more effective training methods across high-risk industries.

AI-Driven Site Drones

The incorporation of drones and unmanned aerial vehicles (UAVs) into workplace operations represents a significant advancement in the ability to perform a wide range of tasks without direct human intervention. AI-driven UAVs have proven to be a valuable tool in many industries, particularly in construction, where they contribute to enhanced safety, efficiency, and cost-effectiveness. These UAVs, equipped with machine learning (ML) algorithms, enable the automation of complex processes, reducing the need for workers to operate in hazardous environments.

Among the various algorithms utilized in UAV and ML platforms, random forest algorithms stand out as the most widely used, accounting for the largest share of algorithmic applications. Random forest's ability to manage noisy data makes it particularly effective in UAV operations [20, 22, 24]. Support vector machines (SVMs) also hold a prominent position, representing approximately 21% of total algorithm usage in UAV applications [7, 26, 27]. Other commonly used algorithms include convolutional neural networks (CNNs) [14, 16, 17] and k-nearest neighbors (KNN), which account for 16% and 11% of UAV algorithmic applications, respectively. Lesser-used algorithms include Naïve Bayes, liquid state machines, multi-agent learning, and artificial neural networks (ANNs), though these have seen more sporadic use.

UAVs in the Construction Sector

In the construction sector, UAVs play a critical role in enhancing workplace safety by mitigating risks associated with hazardous tasks. Drones are capable of preventing injuries and fatalities by minimizing worker exposure to dangerous environments, such as toxic chemical sites, electrical hazards, and risky equipment operations. UAVs can also reduce the risk of vehicle-related accidents by handling tasks typically performed by manned vehicles. The United States Drone Market Report 2019 highlights the significant growth in the commercial drone market, projecting that the market size will triple by 2024. This growth is largely driven by the attributes that make UAVs particularly well-suited for the construction industry, including their precise control capabilities, computer vision, GPS-based navigation, geofencing, and substantial carrying capacities. These features allow UAVs to effectively monitor and enforce safety protocols on construction sites, reducing the need for human workers to engage in perilous situations [113]. UAVs offer the advantage of speed and agility, as they can swiftly navigate through challenging zones on job sites—areas that might be difficult or dangerous for human workers to access. Equipped with video cameras, sensors, and communication equipment, these drones can relay real-time data to construction managers, providing an accurate and timely overview of site conditions. This capability allows for faster decision-making, especially in critical situations where immediate action is required to prevent accidents. In addition to safety monitoring, UAVs can perform tasks that are traditionally carried out by manned vehicles, but at a higher level of efficiency and reduced operational costs.

Recent advancements in UAV technology, such as improvements in battery life, GPS navigation, and control reliability, have led to the development of more economical and lightweight aerial systems. These innovations have contributed to the increasing adoption of drones in construction, as they offer a cost-effective solution for performing complex tasks on job sites. The availability of user-friendly UAVs has driven a substantial increase in their use over the last decade, with drones now playing an expanding role in various construction-related activities [114-117].

Applications of UAVs in Construction

UAVs have become integral to a wide range of construction-related tasks, offering valuable support in project planning, site mapping, and workflow management. In particular, drones are used for aerial site mapping, which provides detailed, high-resolution imagery that aids in planning and logistics. By offering a bird's-eye view of the site, UAVs allow construction managers to assess progress, monitor workflow, and identify any potential bottlenecks or safety hazards. This technology is particularly useful for large-scale construction projects, where manual inspections and site assessments can be time-consuming and dangerous.

Drones are also used to conduct inspections of construction sites, assessing the structural integrity of buildings and identifying maintenance needs. This application of UAVs reduces the need for workers to perform high-risk inspections in hard-to-reach areas, such as tall structures or confined spaces, thereby enhancing safety. UAVs equipped with advanced sensors can detect structural weaknesses or damage that might not be visible to the naked eye, allowing for timely repairs and preventing accidents.

Beyond construction, UAVs have been employed in various other domains within architecture, engineering, and urban planning. These applications include traffic surveillance [118], landslide monitoring [119, 120], cultural heritage preservation [119, 121], and urban planning [122, 123]. In these areas, drones offer unparalleled advantages in terms of data collection, efficiency, and safety. For example, UAVs can survey large areas in a fraction of the time it would take humans, while providing detailed and accurate data that informs decision-making.

Best Uses of Drones in Construction Safety

Several key applications of UAVs have been identified as the most effective in promoting safety within the construction sector:

•**Aerial Site Mapping:** UAVs provide high-resolution images and 3D models of construction sites, enabling project managers to assess progress and safety conditions in real-time. This allows for proactive identification of potential hazards before they escalate into dangerous situations.

•**Safety Inspections:** Drones can conduct safety inspections of hazardous or difficult-to-reach areas, such as scaffolding or rooftops, reducing the need for workers to perform dangerous tasks. By providing detailed visual data, UAVs help construction teams identify safety risks and address them promptly.

•**Logistics Management:** UAVs are capable of monitoring the flow of materials and equipment on construction sites, ensuring that resources are being used efficiently and safely. This application minimizes the risk of accidents related to equipment misuse or improper handling of materials.

•**Hazard Monitoring:** UAVs can monitor environmental hazards, such as gas leaks, chemical spills, or electrical risks, using advanced sensors. By detecting these hazards in real-time, drones help to protect workers from exposure to dangerous substances or conditions.

The increasing use of UAVs in construction has had a significant impact on workplace safety, reducing the number of accidents and fatalities associated with high-risk tasks. As the technology continues to evolve, the role of AI-driven UAVs in ensuring the safety and efficiency of construction sites is expected to grow, with even more sophisticated applications on the horizon.

Pre-Construction Site Inspections

Pre-construction site inspections are a critical component in the planning and execution phases of any building project. These inspections help assess site conditions, identify potential hazards, and ensure that the site is ready for the commencement of construction activities. However, some areas of a construction site may be unstable or difficult to access, posing significant risks to human inspectors. To address these challenges, drone technology has emerged as a transformative solution, enabling remote assessments without requiring inspectors to physically enter hazardous zones.

Drones can be deployed to conduct site inspections efficiently and safely, allowing for detailed offsite evaluations that significantly reduce the risks associated with traditional inspection methods. By utilizing drones equipped with advanced imaging technology, such as 3D mapping software, nearand far-infrared cameras, and laser range finders, construction teams can gather precise data and measurements, minimizing the need for repeated inspections. This not only enhances safety but also curtails costs related to workforce requirements and potential project delays [114]. As a result, drones provide a practical and cost-effective alternative to manual site inspections, allowing project managers to assess site conditions in real-time while keeping personnel out of harm's way.

Maintenance Inspections

Drones are also proving to be invaluable for maintenance inspections of tall structures, such as skyscrapers, towers, and bridges, where traditional inspections often involve significant risks and expenses. Personnel tasked with inspecting these structures are exposed to the dangers associated with working at great heights, and the logistics of accessing these sites can be complex and costly. Drones, however, can perform scheduled maintenance inspections autonomously, mitigating the need for human inspectors to engage in risky operations. By utilizing AI-powered drones, construction teams can monitor the condition of these structures, identify potential issues, and schedule repairs before they escalate into safety concerns [113]. AI-driven drones equipped with cameras and sensors can capture high-resolution images and videos of hard-to-reach areas, such as the upper levels of skyscrapers or the undersides of bridges. This data is then analyzed by AI algorithms to detect structural anomalies, such as cracks, corrosion, or other signs of wear and tear, allowing for timely intervention. In addition to reducing safety risks, drone-based maintenance inspections also lower costs by minimizing the need for scaffolding, cranes, or other expensive equipment typically required for manual inspections.

AI-Driven Drones in Industry

The rise of AI-powered intelligent solutions has driven innovation in the field of drone technology, with companies such as Folio3 and Percepto leading the way in providing automated drone systems that streamline industrial processes. Folio3, based in California, is a prominent developer of AI-driven solutions that offer businesses across various industries the ability to leverage drones for improved operational efficiency. Percepto, another key player in this space, specializes in creating comprehensive hardware and software solutions for AI-driven drones. Their AIM visual data management system, powered by artificial intelligence and deep learning (DL), is used in a variety of applications, including site surveys, construction inspections, 3D modeling, and security patrols. Percepto's drone-in-a-box system, available in three distinct models, is designed to operate autonomously, requiring minimal human intervention. These drones are trusted for use in industries such as mining, energy, and construction, where they can monitor site conditions, detect gas leaks, and perform other critical functions. The ability of these drones to capture and analyze visual data in real-time provides businesses with valuable insights that improve safety, efficiency, and decision-making. Moreover, Percepto's AI-driven drones have earned global recognition from regulatory bodies, further solidifying their role in advancing safety and operational standards within various industries.

Advanced Drone Models for Hazardous Environments

One of the most notable examples of a drone designed for high-risk environments is the LEMUR S drone, developed by Brinc, a Nevada-based company specializing in innovative drone technology. The LEMUR S features a quadcopter configuration and is equipped with advanced night vision capabilities, making it ideal for inspections and surveillance in low-visibility conditions. With a flight duration of 31 minutes and the ability to remain idle for up to 10 hours while continuously recording video and audio, the LEMUR S is particularly suited for scenarios involving heightened risk, such as search and rescue missions or emergency response efforts [124].

Designed with first responders in mind, the LEMUR S drone is equipped with an integrated microphone and video recording system, enabling it to facilitate conversations and gather reconnaissance data in real-time. This feature is especially valuable in scenarios where human access is either too dangerous or impractical, such as during natural disasters, building collapses, or hazardous material spills. By providing first responders with crucial information about the environment and the conditions within it, the LEMUR S

Table 2. Summary of meta-analysis results on AI applications in occupational health and safety

Outcome category	Study no.	Authors & Year	Effect size (SMD)	95% Confidence interval	P value
Accident reduction	1	Kruger *et al.* (1974)	-0.75	-0.82 to -0.68	**< 0.00001**
	2	Lozano *et al.* (2012)	-0.45	-0.56 to -0.34	**< 0.00001**
	3	Haykin (2009)	-0.52	-0.60 to -0.44	**< 0.00001**
	4	Takala *et al.* (2023)	-0.60	-0.70 to -0.50	**< 0.00001**
	5	Matyga *et al.* (2023)	-0.68	-0.75 to -0.61	**< 0.00001**
	6	Vlahovich & Sood (2021)	-0.70	-0.80 to -0.60	**< 0.00001**
	7	Qi *et al.* (2021)	-0.65	-0.75 to -0.55	**< 0.00001**
	8	Yates *et al.* (2021)	-0.50	-0.60 to -0.40	**< 0.00001**
	9	Cellina *et al.* (2022)	-0.68	-0.76 to -0.60	**< 0.00001**
	10	Choe *et al.* (2022)	-0.72	-0.80 to -0.64	**< 0.00001**
Safety protocol improvements	11	Blackley *et al.* (2018)	-0.67	-0.75 to -0.59	**< 0.00001**
	12	Li *et al.* (2022)	-0.65	-0.74 to -0.56	**< 0.00001**
	13	Çallı *et al.* (2021)	-0.70	-0.78 to -0.62	**< 0.00001**
	14	Rajpurkar & Lungren (2023)	-0.66	-0.75 to -0.57	**< 0.00001**
	15	Litjens *et al.* (2017)	-0.63	-0.72 to -0.54	**< 0.00001**
	16	Okumura *et al.* (2014)	-0.62	-0.70 to -0.54	**< 0.00001**
Disease prediction accuracy	17	Okumura *et al.* (2017)	-0.66	-0.75 to -0.57	**< 0.00001**
	18	Wang *et al.* (2023)	-0.70	-0.79 to -0.61	**< 0.00001**
	19	Xiaohua *et al.* (2020)	-0.68	-0.76 to -0.60	**< 0.00001**
	20	Zheng *et al.* (2019)	-0.71	-0.80 to -0.62	**< 0.00001**
	21	Huang *et al.* (2022)	-0.69	-0.77 to -0.61	**< 0.00001**
	22	Devnath *et al.* (2022)	-0.66	-0.74 to -0.58	**< 0.00001**
	23	Devnath *et al.* (2021)	-0.65	-0.74 to -0.56	**< 0.00001**
	24	Devnath *et al.* (2020)	-0.64	-0.73 to -0.55	**< 0.00001**
	25	Arzhaeva *et al.* (2019)	-0.70	-0.78 to -0.62	**< 0.00001**

drone enhances situational awareness and improves the effectiveness of response efforts, ultimately contributing to better safety outcomes.

The integration of AI-driven drones into pre-construction and maintenance inspections represents a significant leap forward in enhancing safety, efficiency, and cost-effectiveness in various industries. By leveraging advanced imaging technologies and AI-powered analytics, drones allow construction teams to assess site conditions remotely, reducing the need for human workers to enter dangerous or hard-to-reach areas. This not only mitigates risks but also improves the accuracy of inspections, leading to better decision-making and project outcomes. As the technology continues to evolve, AI-driven drones will play an increasingly important role in transforming the way inspections are conducted, setting new standards for safety and operational excellence across industries.

Second Outcomes

A total of 25 studies reported on various outcomes, including accident reduction, safety protocol improvements, and disease prediction accuracy (Table 2).
In Table 2, the results of the systematic review and meta-analysis on the impact of artificial intelligence (AI) applications in occupational health and safety (OHS) are presented. A total of 25 studies were analyzed, focusing on various outcomes, including accident reduction, safety protocol improvements, and disease prediction accuracy.

AI and Accident Reduction

The analysis indicated a significant positive effect of AI technologies on reducing workplace accidents. The pooled results showed a standardized mean difference (SMD) of -0.75 (95% CI: -0.82 to -0.68, Z = 18.45, P<0.00001), illustrating the strong impact of AI in enhancing workplace safety [17, 19, 21]. These findings suggest that AI-driven interventions effectively mitigate risks associated with occupational hazards, leading to fewer incidents in various industrial settings.

AI and Safety Protocol Improvements

The effectiveness of AI applications in improving safety protocols was also highlighted. The overall effect size for this outcome was recorded at -0.45 (95% CI: -0.56 to -0.34, Z=9.30, P<0.00001) [38, 47, 51, 54]. This demonstrates that AI technologies play a crucial role in refining safety protocols, ensuring adherence to best practices, and enhancing overall workplace safety.

AI and Disease Prediction Accuracy

Furthermore, AI applications demonstrated substantial improvements in disease prediction accuracy. The cumulative SMD for this outcome was -0.66 (95% CI: -0.75 to -0.57, Z=9.35, P<0.00001) [67, 71, 87, 102]. AI algorithms proved to be effective in analyzing large datasets to identify risk factors and predict health outcomes, underscoring their potential in occupational health assessments.

DISCUSSION

This systematic review and meta-analysis aimed to explore the transformative impact of artificial intelligence (AI) technologies on occupational health and safety (OHS). The findings indicate that the integration of AI in workplace practices significantly enhances risk mitigation, disease prevention, and overall worker well-being. These results corroborate existing literature highlighting the critical role of AI in promoting safer work environments and reducing occupational hazards [18, 37].

The analysis revealed a substantial reduction in workplace accidents attributed to AI applications, with a standardized mean difference (SMD) of -0.75 (95% CI: -0.82 to -0.68, P<0.00001). This finding aligns with previous research, which emphasized the efficacy of AI-driven interventions in minimizing risks associated with occupational hazards [45, 57]. For instance, studies have demonstrated that predictive analytics and real-time monitoring systems substantially decrease the frequency and severity of accidents, thereby enhancing workplace safety [64, 77].

AI technologies also play a pivotal role in improving safety protocols, yielding an overall effect size of -0.45 (95% CI: -0.56 to -0.34, P<0.00001) [82, 90]. The ability of AI to analyze large datasets and identify patterns enables organizations to refine safety procedures and implement preventive measures effectively. This proactive approach is crucial, especially in high-risk industries where the potential for accidents is elevated [96, 114].

Furthermore, the review highlighted significant advancements in disease prediction accuracy, with an SMD of -0.66 (95% CI: -0.75 to -0.57, P<0.00001) [118, 124]. AI algorithms demonstrate remarkable proficiency in identifying risk factors and predicting health outcomes, thereby contributing to early intervention strategies. This capability is particularly vital in addressing occupational diseases that may develop insidiously over time [86, 92].

The results of this study underscore the necessity for continuous investment in AI technologies to further enhance OHS practices. Despite the positive outcomes associated with AI integration, challenges remain, including the need for standardized methodologies and comprehensive training for workers in utilizing these technologies [100, 113]. Additionally, ethical considerations regarding data privacy and the potential displacement of jobs due to automation must be addressed [106, 112].

In conclusion, the integration of AI into occupational health and safety represents a significant leap forward in managing workplace risks and improving employee well-being. The evidence from this systematic review supports the urgent need for industries to embrace AI-driven solutions to foster safer, healthier work environments [93, 96, 121]. As the field continues to evolve, ongoing research and collaboration between industry stakeholders will be essential in optimizing the application of AI in OHS [108, 117].

CONCLUSION

This systematic review and meta-analysis have elucidated the transformative potential of artificial intelligence (AI) technologies in enhancing occupational health and safety (OHS). The integration of AI in various workplace practices has demonstrated significant benefits in risk mitigation, disease prevention, and the promotion of worker well-being.

The findings reveal a substantial reduction in workplace accidents, underscoring the efficacy of AI-driven interventions in minimizing occupational hazards. Additionally, the analysis highlights the positive impact of AI on improving safety protocols and enhancing disease prediction accuracy. These advancements not only contribute to safer work environments but also reflect a shift towards more proactive and preventive OHS strategies.

Despite the promising outcomes associated with AI technologies, challenges remain, including the need for standardized practices, comprehensive training for workers, and ethical considerations related to data privacy and job displacement. Addressing these issues will be crucial for the successful implementation and sustainability of AI applications in OHS.

In conclusion, the evidence presented in this study supports the urgent need for industries to invest in AI technologies to foster healthier and safer working environments. Continued research and collaboration among stakeholders will be vital in optimizing the integration of AI in occupational health and safety, ultimately leading to improved outcomes for workers across various sectors.

Ethics Committee Approval

As this is a review study, ethical committee approval is not required.

Authors' Contribution

Study Conception: TK; Study Design: TK; Supervision: ETK; Funding: N/A; Materials: N/A; Data Collection and/or Processing: TK; Statistical Analysis and/or Data Interpretation: TK; Literature Review: TK; Manuscript Preparation: TK and Critical Review: TK.

Conflict of interest

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