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Article

The advancement of Artificial Intelligence (AI) in Occupational Health and Safety (OHS) across high-risk industries

Priyank Trivedi[1,*], Fahad M. Alqahtani[2,*]

[1] Department of Civil Engineering, Indus Institute of Technology & Engineering, Indus University, Ahmedabad 382115, India
[2] Department of Industrial Engineering, College of Engineering, King Saud University, Riyad 11421, Saudi Arabia
*** Corresponding authors:** Priyank Trivedi, priyanktrivedi.cvl@indusuni.ac.in; Fahad M. Alqahtani, afahad@ksu.edu.sa

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Abstract: This research explores the advancement of Artificial Intelligence (AI) in Occupational Health and Safety (OHS) across high-risk industries, highlighting its pivotal role in mitigating the global incidence of occupational incidents and diseases, which result in approximately 2.3 million fatalities annually. Traditional OHS practices often fall short in completely preventing workplace incidents, primarily due to limitations in human-operated risk assessments and management. The integration of AI technologies has been instrumental in automating hazardous tasks, enhancing real-time monitoring, and improving decision-making through comprehensive data analysis. Specific AI applications discussed include drones and robots for risky operations, computer vision for environmental monitoring, and predictive analytics to pre-empt potential hazards. Additionally, AI-driven simulations are enhancing training protocols, significantly improving both the safety and efficiency of workers. Various studies supporting the effectiveness of these AI applications indicate marked improvements in risk management and incident prevention. By transitioning from reactive to proactive safety measures, the implementation of AI in OHS represents a transformative approach, aiming to substantially reduce the global burden of occupational injuries and fatalities in high-risk sectors.

Keywords: operational health and safety; high risk industry; artificial intelligence; deep learning; computer vision

1. Introduction

Annually, the global workforce experiences 2.3 million fatalities due to occupational incidents and diseases, which breaks down to more than 6000 deaths each day (International Labour Organization, 2011). Reports indicate that around 340 million workplace accidents occur yearly, affecting 160 million individuals with occupational illnesses. Notably, these diseases are a significant cause of worker mortality, with hazardous substance exposure accounting for approximately 651,279 deaths annually (International Labour Organization, 2011). The construction sector, in particular, records a higher frequency of accidents than other fields, with over 150,000 incidents and injuries reported each year. This sector is about 70% more likely to report injuries compared to others (Tyrrell, 2021). The Global Disease Burden reveals that diseases such as pneumoconiosis (CWP), silicosis, and asbestosis have been responsible for 125,000 deaths of coal workers (Lozano et al., 2012). While the counts of pneumoconiosis has declined globally since 2015, the disease still affects a substantial number of individuals (James et al., 2018; Vos et al., 2015). Moreover, the death toll from these diseases remains high, with more than 21,000 people dying annually since 2015 (Qi et al., 2021).

The implementation of Occupational Health and Safety (OHS) management strategies is critical to protect employees from workplace hazards and illnesses (Uhrenholdt Madsen et al., 2020). OHS represents a structured method adopted by organizations to ensure employee safety, health, and welfare during work. Despite these efforts, complete prevention of workplace incidents is challenging, necessitating ongoing dedication and enhancement to better safeguard workers. Investments in worker safety, health, and welfare are substantial but yield significant benefits, including reduced compensation claims, legal expenses, and lower insurance costs (Tang, 2024). Moreover, these practices enhance employee relations and morale, as workers feel valued and cared for by their employers. This not only fosters a positive work environment but also enhances a company's market standing, reputation, and trust (Tang, 2024). Increasingly, companies are integrating OHS management systems to ensure the safety and health of their workforce. Central to OHS management is risk management, which focuses on identifying, evaluating, and managing risks associated with work activities and environments (Kuok Ho et al., 2018). Its goal is to minimize the incidence and impact of occupational injuries, diseases, and incidents, thereby boosting overall OHS performance (Kuok Ho et al., 2018). Effective risk management includes defining the scope, context, and criteria based on organizational objectives, expectations, and challenges (Gül and Ak, 2018). It emphasizes stakeholder engagement through communication and consultation, gathering their insights, feedback, and support for managing workplace risks. The risk management process involves conducting risk assessments to pinpoint and evaluate occupational hazards using suitable methodologies and tools (Gül and Ak, 2018). After conducting an assessment, risks are reduced or minimized based on the hierarchy of control methods. These methods include elimination and substitution, controls of engineering systems, control over administrative process, and the uutilization of personal protective equipment. The order of priority for implementing these methods is elimination and substitution first, followed by engineering controls, administrative controls, and finally the use of personal protective equipment. Further, timely monitoring and compliance checks are essential for ensuring strong risk reduction. This process is periodically reviewed to pinpoint improvement opportunities and enhance organizational learning (Gül and Ak, 2018). Nevertheless, traditional OHS risk management practices may struggle to capture all significant workplace risks, occasionally leading to non-compliance with established OHS standards and regulations.

The reliance on human labor to pinpoint occupational hazards may result in the underestimation of risks, especially in hard-to-reach areas. Artificial intelligence (AI) encompasses the capabilities of computer systems or robots to execute tasks, which conventionally mandating human intellect. The said tasks incorporate language comprehension, image identification, decision-making, and problem-solving (Moore, 2019). AI's utility spans multiple sectors such as healthcare, education, entertainment, and finance, enhancing human performance and productivity. This enhancement is evident through the automation of monotonous or hazardous tasks, increased accuracy, efficiency, and the generation of innovative insights and solutions (Moore, 2019). AI-enabled devices, like robots or drones, are increasingly used for inspection, maintenance, or repair operations in perilous settings such as mines, power plants, and construction sites, enhancing safety and efficiency. Moreover, AI supports the extensive collection and analysis of worker's data concerning the physical situation, mental stability, and emotional well-being, thereby facilitating enhanced monitoring and performance improvement. With this data, AI systems can provide early warnings and interventions to help prevent conditions like burnout, depression, or anxiety (Moore, 2019). AI also plays a pivotal role in OHS training by crafting realistic, immersive simulation scenarios, particularly for emergency response, which significantly enhances the training experience for workers. Such simulations allow workers to better visualize and effectively manage various emergency situations at work. As AI technology advances and its application broadens across sectors, this review aims to:

- systematically outline the progress in AI applications within OHS risk management, specially within higher risk area such as the construction, mining, and oil and gas industries.
- elaborate a deeper understanding of AI's role and efficacy in OHS risk management and discusses.
- enlightens AI-driven technologies for reshaping workplace safety by preventing occupational diseases and enhancing safety measures.

2. Application of AI across high-risk industries

AI has been progressively incorporated into various applications through machine learning (ML), computer vision (CV), knowledge-based systems, and natural language processing (NLP) (Abioye et al., 2021). **Figure 1** represents this progressive AI system. Each of these forms of AI offers distinct advantages and tools in handling and analyzing data for decision-making, such as

- Computer Vision: This technology relies on capturing images through specialized cameras and using advanced algorithms to analyze these images for insightful decision-making. It plays a crucial role in environments where visual monitoring and precision are required (Hammoudeh et al., 2022).
- Knowledge-Based Systems: These systems function by integrating existing knowledge into an inference engine, coupled with a user interface that facilitates interaction with the system. The system is a reservoir of expert knowledge and past case studies that aid in decision-making (Kuok Ho et al., 2018). It can be segmented into various types:
    a) Expert Systems: Utilize a knowledge base of specific experts or experiences within an individual sector to emulate decision-making processes for solving complex problems of OHS (Hurtado et al., 2022).
    b) Case-Based Reasoning Systems: These systems analyze experiences or past cases stored in the knowledge base for critical analysis, interpretation, or prediction. Selection of cases relies heavily on OHS expert knowledge (Su et al., 2019).
    c) Intelligent Tutoring Systems: Designed to simulate human tutors, these systems provide tailored instructions or feedback, making them particularly useful for OHS training (Gonzalez et al., 2007).

d) Database Management Systems: Serve as the backbone for data storage, organization, and manipulation, supporting other systems by ensuring data is structured and consistently managed (Çalış and Buyukakinci, 2019).

- Natural Language Processing (NLP): NLP develops understanding and manipulating power of human language into the machines, whether in text or spoken form. This branch of AI is utilized for various purposes, including speech-to-text conversion, natural language generation and understanding, and text summarization (Bieri et al., 2024).

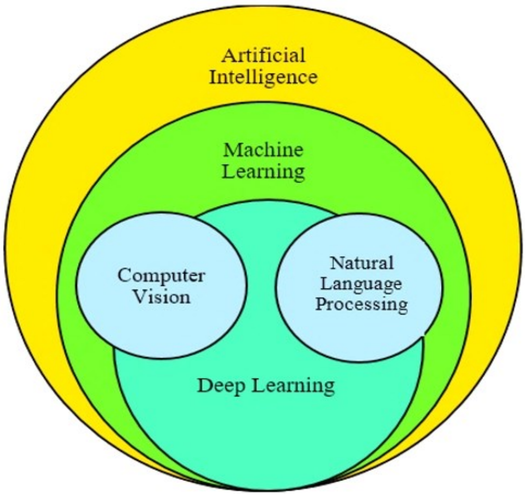

Figure 1. Progressing subcomponents of AI systems.

AI's role in OHS risk management is multifaceted. By employing AI technologies such as computer vision and knowledge-based systems, it is possible to continuously evaluate workplace environments through sensors, cameras, and wearable technologies. This constant surveillance aids in providing timely warnings to workers when they are at risk of significant hazards (Adem et al., 2020). Moreover, AI facilitates the automation of dangerous or physically demanding tasks by using robots or collaborative robots (cobots), which can significantly reduce the exposure of workers to hazardous conditions. This integration of AI in OHS practices not only enhances worker safety but also boosts efficiency and productivity by reducing the potential for accidents and injuries. AI significantly mitigates the risks that workers face by automating tasks that are hazardous or physically demanding. The use of AI supports the analysis of vast quantities of occupational data, which facilitates the identification of patterns, trends, and potential OHS risks. By leveraging machine learning algorithms, AI systems can continually evolve from and adjust to new data, thereby enhancing its ability to forecast potential hazards before they become imminent threats. This predictive capability not only helps in preempting accidents and injuries but also supports proactive measures in managing workplace safety. This approach marks a substantial shift from reactive OHS practices to a more dynamic, predictive strategy, optimizing safety protocols and reducing risk exposure for workers.

2.1. Adopted method to evaluate AI across high-risk industries

To gather a comprehensive overview of the progression in detecting occupational diseases and the technological interventions in industrial environments, an extensive literature search was conducted. The databases utilized for this research included Embase, PubMed, and Google Scholar. The starting point for the search was set to 1974–1975, the year when digital methodologies were first employed in the analysis of job-related lung illnesses with the help of chest radiographs, marking a significant milestone in the field. The keywords selected for the search encompassed a range of terms related to the application of technology in occupational health. These terms included "Artificial Intelligence," "Occupational Health and Safety," "Health Automation," "Safety Automation," "Workplace safety", "Workplace Monitoring," "Occupational Disease Detection," "Incident Prevention," "Wearable Technology," "Workplace Injuries". These terms were used in various combinations to maximize the breadth and depth of the search. To refine the search further, additional keywords such as "Artificial Intelligence", "Deep Learning," "Computer Vision," and "Natural Language Processing" were also employed. This methodical approach ensured the capture of relevant advancements and trends in the field over the decades, highlighting both chronological developments and technological innovations in occupational disease detection within industrial settings.

3. AI for OHS in high-risk industries

This section is divided into three subheadings. Each of the three subheadings provides a comprehensive application of AI for different high-risk industries.

3.1. AI for construction industry

The construction industry ranks as one of the most perilous fields in terms of OHS risks. Notable hazards in this sector include traumatic injuries from falls, electrical shocks, machinery, tools, and vehicles; exposure to hazardous chemicals such as cement, asbestos, dust, and solvents; physical dangers from noise, vibration, and extreme temperatures or radiation; and ergonomic risks related to poor posture, manual labor, or repetitive movements (Gunduz and Laitinen, 2018). These hazards can lead to a range of health issues for construction workers, including musculoskeletal disorders (Boschman et al., 2012; Reddy et al., 2016), respiratory conditions (Boadu et al., 2023), noise-induced hearing loss (Mazlan et al., 2018), dermatitis. **Figure 2** depicts the flowchart of AI's application in the construction sector, with an emphasis on OHS.

AI technology has opened new pathways to mitigate these risks in the construction industry. Zhang et al. (2015) devised a framework that identifies fall hazards early in the project planning stages, utilizing algorithms that automatically check compliance with safety regulations. This system integrates safety measures into building information modeling and was evaluated using a construction project model, showing strong capabilities in detecting unprotected slab edges and suggesting the installation of guardrail systems as per safety guidelines. The tool also offers recommendations for the installation and removal tasks, providing options and procedures to enhance fall protection during the design and planning phases (Zhang et al., 2015). However, this framework must be continually verified to confirm the effectiveness of its fall protection suggestions, especially in rapidly changing project environments, and it requires further refinement in detail (Zhang et al., 2015). In another innovative approach, a study introduced an automated, cloud-based system for real-time safety monitoring at construction sites (Park et al., 2016). This system employs Bluetooth low-energy technology for location tracking and integrates with an information model to facilitate hazard identification and safety communication via a cloud platform. It has proven effective in identifying unsafe site conditions and assessing risk impacts on workers based on their acute locations (Park et al., 2016). Unlike traditional computer vision, this system uses Bluetooth for positioning, allowing the algorithm to evaluate the exposure risks without generating visual data. Additionally, a separate initiative combined with radio-frequency identification integrated with building information modeling (BIM) to manage construction sites more effectively. This system enhances site safety management through advanced localization and visualization capabilities (Fang et al., 2016). Further afield, in the power infrastructure sector, ML techniques such as boosted trees and deep learning have been applied to scrutinize injury causes and forecast potential incidents (Oyedele et al., 2021). This predictive approach, particularly through deep feed forward neural networks, has demonstrated superior performance in anticipating safety issues, thereby enhancing risk management (Oyedele et al., 2021).

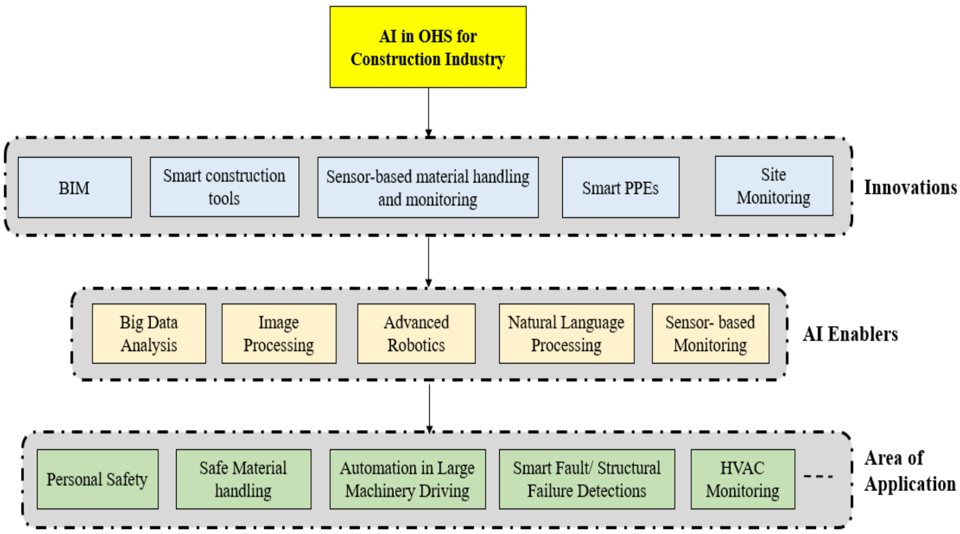

Figure 2. AI for construction industry.

Moreover, the adoption of BIM has revolutionized safety management by integrating it into the preliminary design and planning phases of construction projects. An automated feature has been crafted to simulate and visualize worker movements on scaffolds using building information models (Kim et al., 2016). This system includes algorithms designed to detect safety risks associated with scaffold work, aiding in the development of preventive strategies. This capability can be integrated into BIM software as an add-on, providing a unique benefit of identifying safety hazards that may be missed by project managers (Kim et al., 2016). Additionally, computer vision has become increasingly prominent in construction safety management. Beyond the mentioned applications, Zhang introduced a machine vision technology aimed at enhancing safety in civil engineering projects. This technology combines real-time target detection, spatial analysis between construction environments and targets, and an early warning system (Zhang, 2021). It is configured to activate alerts when a predefined unsafe condition is detected, thus bolstering safety measures on site. **Table 1** summarizes some applications of AI in Construction industry.

Table 1. Some application of AI in construction industry.

AI Technique	Application	Remark	Reference
ANN, Image Processing	Detection of material strength	New method for concrete strength testing using image processing techniques	(Dogan et al., 2017)
Big Data Analytics, Image processing	Observation of workers' behavior on construction sites	Utilization of big data enhances safety and efficiency in construction through behavior analysis	(Guo et al., 2016)
Deep Learning	Automatic recognition of water leakage areas	Deep learning techniques effectively identify water leakage areas in shield tunnel linings, enhancing maintenance and safety protocols.	(Xue et al., 2020)
Augmented Reality, Image Recognition	Hazard avoidance in construction	Wearable AR devices improve safety by enabling real-time hazard detection	(Kinam et al., 2017)
Stochastic Modeling, Real-Time Location Systems	Prediction of safety states on construction sites	Real-time modeling provides dynamic predictions, increasing site safety	(Li et al., 2016)
Bayesian Network	Intelligent building fire risk assessment	The classification model enhances trust and accuracy in assessing fire risks in intelligent buildings, promoting safer building management strategies.	(Wu and Chen, 2022)
ST-GCN and YOLO	Identification of interaction behaviors of workers	The combination of ST-GCN and YOLO effectively identifies interaction behaviors among construction workers, enhancing workplace safety and operational efficiency.	(Li et al., 2023)
Integration of Detection and Tracking	Improved localization of workers in video frames	By integrating detection and tracking techniques, the study enhances the accuracy of localizing construction workers in video surveillance, improving safety monitoring on construction sites.	(Park and Brilakis, 2015)

3.2. AI for mining industry

The mining industry is characterized by its high-risk nature, with frequent incidents involving heavy equipment, explosives, and dangerous chemicals. Such incidents often lead to injuries, fatalities, or permanent disabilities. Workers in this sector are also exposed to dust, gases, and fumes that can cause serious lung conditions including silicosis, coal workers' pneumoconiosis, asbestosis, and various cancers. Additionally, the sector is notorious for its high noise levels, which can impair hearing and result in industrial deafness (Sun and Azman, 2018). Consequently, managing these risks is vital, and the integration of AI could enhance the effectiveness of these management efforts. **Figure 3** depicts the flowchart of AI's application in the mining industry, with an emphasis on OHS.

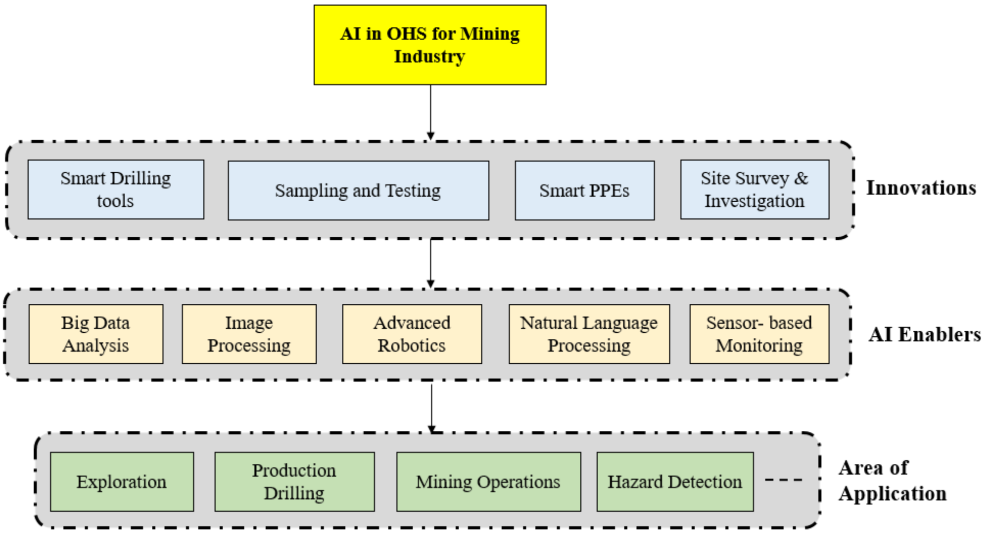

Figure 3. AI for mining industry.

AI is extensively applied throughout the mining lifecycle, encompassing exploration, planning, operation of mobile machines, drilling, blasting, and ore processing (Ali and Frimpong, 2020; Hyder et al., 2019). Recent advances in AI have greatly enhanced automation in machinery and vehicle operations (Ali and Frimpong, 2020; Hyder et al., 2019). Notably, one of the most innovative uses of AI involves developing computer vision-based anti-collision systems. Particular innovation incorporate advance sensor systems, such a high resolution cameras and LIDAR (Shahmoradi et al., 2020), employing complex DL algorithms to monitor and identify the movement of both individuals and machines within mining environments (Imam et al., 2023; Kim and Choi, 2021; Szrek et al., 2020; Wu, et al., 2023). This capability is crucial for enhancing safety, as it enables the provision of immediate warnings and alerts to both operators and workers, potentially preventing accidents and injuries (Szrek et al., 2020). Moreover, the mining sector is increasingly adopting virtual and augmented reality (VR/AR) technologies (Zhang, 2017). Additionally, VR/AR is beneficial for simulating emergency situations, helping to improve workers' response times and overall safety preparedness (Guo et al., 2017).

Furthermore, these technologies facilitate remote monitoring and maintenance tasks, allowing for equipment checks without the physical presence of workers, thereby reducing accident risks. Research conducted by Yedla et al. (2020) has utilized ML technologies such as artificial neural network (ANN), decision trees, and random forests to study mining accident data. These technologies outperformed traditional logistic regression models in predicting the outcomes of such accidents. Key factors influencing the period for which workers are not available for work include their mining experience, shift start times, and the timing of the accident (Yedla et al., 2020). Similarly, in the construction industry, technologies like computer vision coupled with sensor applications are being increasingly adopted. One notable innovation is a Bluetooth-based system designed for underground navigation and monitoring of mining operations, supported by an extensive underground Bluetooth network (Baek et al., 2017). The detection of toxic gases in mines represents a significant challenge, with traditional methods often falling short. To address this, there has been development towards an automated remote monitoring system that utilizes wireless sensor technology. This system employs principles such as Ohm's law and mobile sensing, integrated with AI-driven decision-making (Osunmakinde, 2013). The system, tested in real-world scenarios, aims to replicate the expertise of safety engineers in detecting toxic gas exposure and provides early warnings to mitigate risks (Osunmakinde, 2013). This comprehensive framework combines computer vision and expert systems to enhance risk management practices in underground mining environments. **Table 2** summarizes some applications of AI in Mining Industry.

Table 2. Some application of AI in mining industry.

AI Technique	Application	Remark	Reference
ANN	Approximation of Surface Subsidence due to Rock Mass Drainage	ANNs prove suitable for modeling surface subsidence, offering a reliable method for predicting geological changes.	(Hejmanowski and Witkowski, 2015)
ANN, Fuzzy Inference System	Prediction of Subsidence Risk by FMEA	Combining ANN and Fuzzy systems enhances the prediction accuracy of subsidence risks, improving mining safety.	(Rafie and Samimi Namin, 2015)
Hyperion Image Analysis	Mapping of Iron Ore	Hyperion image analysis effectively maps iron ore distributions, aiding in resource management and extraction strategies.	(Kumari et al., 2014)
ANN	Prediction of Dust Concentration in Coal Mines	ANNs effectively predict dust levels in open cast coal mines, aiding in environmental and health management.	(Lal and Tripathy, 2012)
Internet of Things (IoT)	Early-Warning Safety System for Underground Mines	IoT-based systems enhance safety in underground coal mines through effective event reporting and early warnings.	(Jo and Khan, 2017)
Hybrid CNN-LSTM	Coal mine hazards monitoring and prediction	IoT-based system for real-time monitoring and prediction	(Dey and Chaulya, et al., 2021)
Deep Convolutional Neural Network (CNN)	Secure wireless voice communication for underground mines	Focus on safety and reliability in mine working communication	(Dey and Kumar, et al., 2021)

3.3. AI for oil and gas industry

The oil and gas industry, considered a branch of the broader mining sector, experienced 1,021 workplace accidents in Malaysia in 2023, with 18 of these being fatal. The frequency of accidents was noted at 0.69, and the severity rate reached 17.97 per million man-hours (DOSH, 2023). On a global scale, this sector's average fatal accident rate is 3.0 per 100,000 workers, which is higher than the overall industry rate of 2.3. Predominant fatal accident types internationally include transportation incidents (41%), interactions with objects and equipment (25%), and fires and explosions (15%) (UNDRR, 2024). To reduce this numbers, AI enabled innovation are presented (Desikan and Devi, 2023). **Figure 4** depicts the flowchart of AI's application in the Oil and Gas Industry, with an emphasis on OHS.

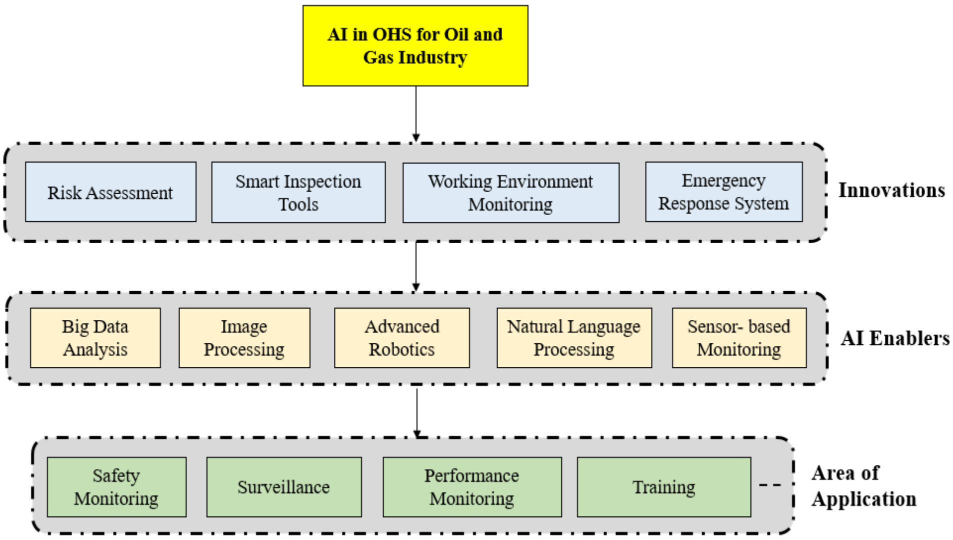

Figure 4. AI for oil and gas industry.

Linear sensor networks, equipped with custom sensor boards and algorithms, have also been implemented to enhance safety in oil and gas operations. Abbas et al. (2021) applied wireless sensor network (WSN) for evaluating gas distribution network. This innovation reduces the cost of operation with high data reliability and reduces the likelihood of direct human contact. Rashid et al. (2015) have innovated a smart wireless sensor network that identifies and evaluates leaks in pipelines using machine learning techniques to analyze negative pressure waves detected by sensors. To further safeguard pipeline integrity, another initiative has combined a GPRS network, the Internet, and wireless sensor networks to monitor terrestrial pipeline cathodic protection systems. This setup ensures the timely collection and transmission of cathodic potential data to control centers for appropriate action (Liu et al., 2015).

Additionally, Jung and Song (2014) utilized wireless sensor networks to create a safety monitoring system for industrial pipe racks, successfully tested in petrochemical facilities. This system evaluates structural stability and offers risk management solutions. Another sensor-based technology was developed to detect propane leaks, successfully identifying 91% of leaks within three days, with an average delay of 108 seconds (Chraim et al., 2016). These sensor-based technologies are increasingly popular in the oil and gas sector because of its capability to deliver real-time, extensive area coverage and rapid hazard detection, which facilitates prompt decision-making. Additionally, an expert system has been proposed to assess OHS and process safety on offshore platforms, providing a risk level index based on various safety aspects (Tang et al., 2018). Moreover, **Table 3** summarized some applications of AI in Oil and Gas Industry.

Table 3. Some application of AI in oil and gas industry.

AI Technique	Application	Remark	Reference
Model-Based Approach	Fault Detection in Chemical Processes	Focuses on transitions and steady-state operations	(Bhagwat et al., 2003a)
Multi-Linear Model	Fault Detection during Process Transitions	Uses multi-linear models for enhanced fault detection	(Bhagwat et al., 2003b)
Robotics	Infrastructure Repair	Robots assisting in maintenance and repair of infrastructure	(Mitchell, 2019)
Artificial Neural Network (ANN)	Foam Drilling maintenance	Predicts hole cleaning effectiveness	(Rooki et al., 2014)
Artificial Neural Network (ANN)	Drilling Operations in Oil Fields	Used for predicting stuck pipe issues in drilling operations	(Shadizadeh et al., 2010)
Wireless Sensor Networks	Monitoring of Gas Distribution Pipelines	Enhances monitoring and safety of pipeline networks	(Abbas et al., 2021)
Wireless Sensor Networks	Gas Leak Detection and Localization	Focus on industrial safety and leak prevention	(Chraim et al., 2016)

4. Occupational disease diagnosis and prevention by AI

Diagnosing occupational illnesses in clinical environments is notably challenging due to the extended latency periods associated with these conditions, including pneumoconiosis, silicosis, asbestosis, lung cancer, and chronic obstructive pulmonary disease (COPD) (Blackley et al., 2018; Vlahovich, 2020). These extended periods often complicate treatment and management. Historicallu, Kruger et al. (1974) screed and evaluated diseases in workers with the utilization of optical fourier transformation. This affort helped workers for maintaining their health by getting the required compensation. Since then, the application of AI and mathematical modelling has taken a novel direction for disease diagnosis. More advancements in similar direction included the use of multilayer perceptron (MLP), multiresolution support vector machine (SVM)-based algorithms, and developments in convolutional neural networks (CNNs) and DL algorithms for enhancing CXR image analysis (Litjens et al., 2017).

Recent advancements in AI, particularly DL, have significantly enhanced the analysis of lung images, revolutionizing the diagnosis processes using plain radiographs (Çallı et al., 2021). AI algorithms excel in interpreting chest X-rays (CXRs), computed tomography (CT) scans, and magnetic resonance imaging (MRI) scans (Shah and Mishra, 2024). They effectively detect and classify anomalies, pinpointing nodules, masses, or disease-specific patterns such as those found in mesothelioma, COPD, and silicosis. For individuals at risk of pneumoconiosis, a CXR is mandatory, highlighting the global health burden this condition places, especially on low- and middle-income countries (Li et al., 2022). Diagnosing conditions of such illness causes due to working conditions requires intricate decision-making processes, presenting substantial challenges for radiologists. AI models have proven to be highly effective in parsing imaging data with precision and accuracy (Cellina et al., 2022).

These advanced AI tools also assist in data augmentation, reducing image noise, and creating synthetic data. Such capabilities produce synthetic lung images closely resembling those of actual patients, providing crucial insights for predicting a worker's health trajectory and limiting hazardous exposures in dust-prone industries. Moreover, Image Processing plays an increasingly essential role in the evaluation of pulmonic diseases, with advancements of viable AI algorithms for chest imaging. These have gained recognition from regulatory authorities and are now available commercially in over 20 countries (Choe et al., 2022).

4.1. Moving normalization by applying Artificial Neural Network (ANN) in X-ray image analysis

Diagnosing occupational lung diseases, according to the ILO, relies on two critical assessment categories: the number and area density classification, and the size of abnormalities within the region of interest (ROI) on a postero-anterior chest X-ray. A primary challenge in analyzing the textures of chest radiographs is the complex "background" created by the overlap of normal anatomical structures. This complexity necessitates that the analysis be somewhat insensitive to background variations. Historical efforts to correct background trends have focused on removing minor ROIs (Katsuragawa et al., 1990). **Figure 5** represents steps to evaluate an X-ray image with ANN.

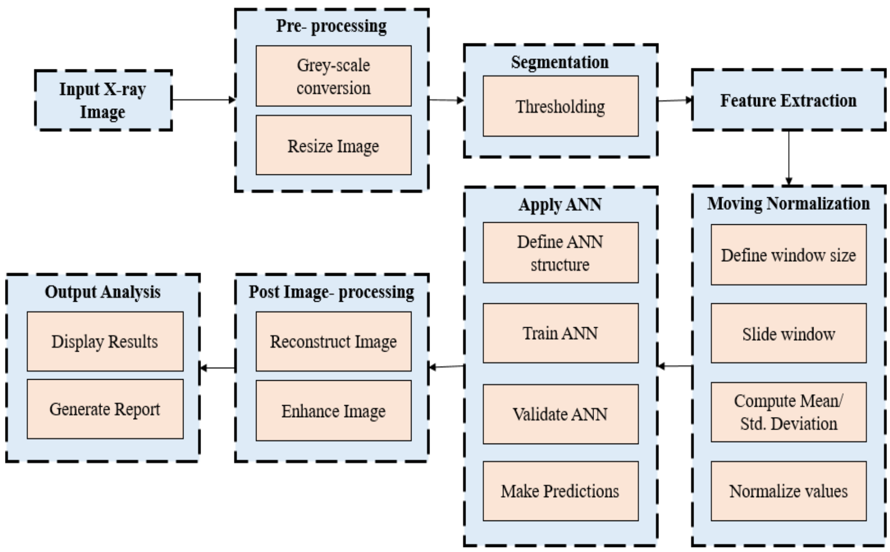

Figure 5. General steps to apply ANN with moving normalization for X-ray image analysis.

Significant advancements have been made by Kondo and Kouda (2001), who utilized a three-layer back-propagation neural network to detect small rounded opacities by filtering out rib shadows and vascular markings in chest X-rays. This neural network approach generated an optimized bi-level ROI image. Their comprehensive evaluation, focused on size and shape analysis, proved that this new method is significantly more reliable than traditional techniques. It employs a 'moving normalization' strategy to eliminate background interference. The algorithm assesses the number and area density of rounded opacities, comparing them against ILO standard X-ray images to produce a classification (Kondo et al., 2000). This type of precise classification carries significant implications for decisions on job reassignments and worker's compensation claims related to pneumoconiosis (Jagoe, 1979; Sishodiya, 2022).

4.2. Deep learning embedded with ANN and CNN for non-textural analysis

ANN techniques have significantly evolved beyond traditional manual texture analysis, also providing substantial time efficiencies. DL techniques have transformed non-texture chest X-ray analysis through automated capabilities. These improvements have greatly enhanced pneumoconiosis classification settings with improved accuracy and efficiency.

Okumura et al. (2014) advanced a pneumoconiosis identification system combining rule-based and ANN methodologies, utilizing three enhancement techniques—window function, top-hat transformation, and gray-level co-occurrence matrix. This approach differentiated effectively between normal and pathological ROIs in CXRs, achieving significant classification accuracy with areas under the curve (AUCs) of 0.93 ± 0.02 and 0.72 ± 0.03 for severe and low-grade pneumoconiosis, respectively. Okumura et al. (2017) further reported diagnostic AUCs of 0.89 ± 0.09 and 0.84 ± 0.12 for both disease grades using a three-stage ANN, underscoring occasional challenges NN algorithms face in learning complex representations from pneumoconiosis CXRs, which can impact their accuracy and broader application effectiveness.

In addition, researchers started modifying CNN architectures to fulfil the special requirements of CXR classification. The use of transfer learning, which involved the utilisation of pretrained convolutional neural network (CNN) models trained on large picture datasets, made significant progress. These models were then fine-tuned specifically for the interpretation of chest X-ray (CXR) images, effectively overcoming the difficulty of having little labelled medical data available (Bozinovski, 2020). This method, while time-consuming and costly, has proven beneficial. Significant strides in pneumoconiosis CXR analysis using CNNs have been made by researchers such as Devnath et al. (2022), Zhang et al. (2021), Wang et al. (2020), and Arzhaeva et al. (2019). These studies typically leverage the ImageNet pretrained CNN model. For pneumoconiosis diagnosis, Zheng et al. (2019) utilized various CNN models including LeNet, AlexNet, and GoogLeNet (Inception-v1 and v2), achieving notable accuracy improvements with the optimized Inception-CF model. Another deep CNN application on one of the largest datasets of 33,493

CXRs demonstrated a 92% accuracy with a very high sensitivity (99%), effectively minimizing missed diagnoses (Xiao et al., 2021). Due to its great sensitivity, this technique is highly recommended for pneumoconiosis screening in workplace wellness evaluations in China. It is capable of detecting almost all cases of the illness. Wang et al. (2020) utilised the Inception-V3 Convolutional Neural Network (CNN) structure and obtained an Area Under the Curve (AUC) value of 87.80 (95% Confidence Interval, 0.811–0.946), demonstrating the effectiveness of Deep Learning (DL) techniques in pneumoconiosis screening. **Figure 6** represents steps to conduct non- textural analysis with CNN.

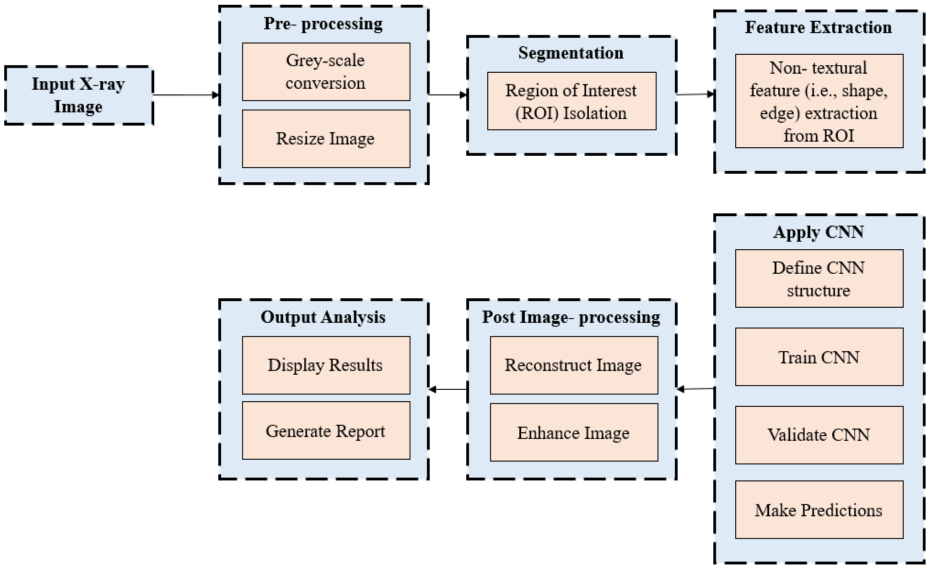

Figure 6. General steps to apply ANN with moving normalization for X-ray image analysis.

4.3. Deep learning for pre-clinical stage classification

Upon diagnosing pneumoconiosis, patients are often found to be in a critical condition, making treatment particularly complex. Early identification of this disease during its preclinical stage is crucial to effectively manage and mitigate its impact. Early detection not only reduces the incidence but also lessens the severity of the condition among workers exposed to its hazards (Qi et al., 2021).

Recent AI-driven research into early-stage detection by Wang et al. (2023) employed an innovative three-stage cascaded learning model. Initially, a YOLOv2 network was used to pinpoint lung areas within digital chest radiography (DR) images. This was followed by the training of six different CNN models aimed at identifying early signs of Coal Workers' Pneumoconiosis (CWP). In the final stage, a hybrid ensemble learning model was developed, employing a soft voting mechanism to integrate results from the six CNNs. The study utilized 1447 digital radiographs from various coal industry workers, including drillers and general laborers. The CNNs trained included models like Inception-V3, ShuffleNet, Xception, DenseNet, ResNet101, and MobileNet. The cascade model demonstrated an AUC of 93.1% and an accuracy rate of 84.7%, indicating a significant advancement in the preclinical screening capabilities for coal workers (Wang et al., 2023).

5. Personal and workspace safety enhancement with AI enabled monitoring

This section briefly describes the application of AI for the enhancement of personal and workspace safety. **Figure 7** represents the major AI driven advancements in the field of personal and workplace safety.

Figure 7. Personal and workplace safety enhancement with AI enabled monitoring.

5.1. Personal safety enhancement and monitoring

5.1.1. Exoskeletons with AI integration

Occupational exoskeletons are designed to minimize the risk of back and shoulder injuries. They aim to support workers and boost safety in the workplace, especially where traditional ergonomic solutions fall short. Workers wearing these devices reported less discomfort, fewer injuries, and reduced workers' compensation costs. Studies have shown that occupational exoskeletons can lessen muscle strain and fatigue during physical activities across various sectors, including logistics, construction, manufacturing, military, and healthcare. Wearable exoskeletons, robotic suits designed to augment limb and joint function, have become instrumental in enhancing productivity and safeguarding the health of workers. Research increasingly supports the adoption of various ANN frameworks in cutting-edge exoskeleton technologies (Nayak and Das, 2020). Furthermore, traditional control techniques are now being merged with smart or adaptive optimization strategies to create robust or hybrid systems (Bonato, 2005). Historically, ANNs have been crucial in the development of biomechatronics and intelligent systems, leading to advancements in intelligent medical devices such as brain-machine interfaces for prosthetics and sophisticated robotic exoskeletons for rehabilitation (Nayak and Das, 2020). Exoskeletons also enable biometric evaluations and post-injury rehabilitation, reducing spinal stress and improving the physical condition of employees (Ajunwa and Greene, 2019).

5.1.2. Personal Protective Equipment (PPE) with AI integration

Considering the safety of workers and the prevalence of workplace accidents, it is essential to update traditional tools and methods to keep pace with evolving technological advancements. Recent research has investigated the application of AI in the manufacturing industry (Li et al., 2017; Podgórski et al., 2016; Sun et al., 2020). This integration not only connects various aspects of the industry but also significantly enhances the safety and security of employees. With the introduction of smart personal PPE and wearable technologies, collecting data about workers and their environment has become possible (Márquez-Sánchez et al., 2021). This approach is data-driven and aims to reduce the frequency of accidents and occupational diseases, thus significantly improving workplace conditions. The evolution of smart PPE has made it possible to monitor critical health indicators and evaluate industrial environments. Various strategies for integrating wearables into workplace environments have been explored, examining how networks of connected devices can help protect individuals. These solutions utilize diverse AI techniques such as neural networks (Raha et al., 2023; Vukicevic et al., 2022), fuzzy logic (Iannizzotto, Lo Bello and Patti, 2021; Márquez-Sánchez et al., 2021; Panja et al., 2023), Bayesian networks (Lisi et al., 2021; Mohammadfam et al., 2017); Nguyen, Tran, and Chandrawinata, 2016, decision trees (Mistikoglu et al., 2015; Tetik et al., 2021) and other hybrid inference models (Loey et al., 2021; Nath et al., 2020). Traditional safety systems in workplaces are designed to meet the specific needs of each company and react only when certain thresholds are exceeded, which is a primarily reactive “action-reaction” model (Shah and Mishra, 2024). This method offers limited adaptability and flexibility in new situations. In contrast, AI systems equipped with learning capabilities employ a different strategy. They operate based on a set of rules and knowledge gleaned from past problem-solving experiences to predict outcomes in new scenarios.

Some innovation like, Smart helmets have revolutionized traditional safety gear by incorporating advanced technology integrated with AI. These helmets are equipped with a comprehensive array of sensors, including GPS, RFID (Radio Frequency Identification), UWB (Ultra-Wideband), and AVM (Around-View Monitor) (Shah and Mishra, 2024). These sensors work together to track the location of workers, monitor their activities, and assess both the environment and personal health metrics (Campero-Jurado et al., 2020; Kuhar et al., 2021). Similarly, Smart boots represent a proactive step in enhancing workplace safety by utilizing artificial intelligence to detect hazardous conditions such as slippery surfaces, identify obstacles, and monitor environmental factors. These innovative boots go beyond basic protection by showcasing how AI can transform occupational safety norms, underlining a commitment to employee well-being. This kind of AI enabled Smart PPEs include features to reduce the chances of human error such as fall detection, geofencing, built-in nocturnal flashlights, local data storage for on-the-spot analysis, a two-way alert communication system, and tactile feedback for immediate user notification (Lee et al., 2022; Sanchez et al., 2020).

5.2. Workspace safety enhancement and monitoring

The transformative technological advancements in computer vision, virtual reality (VR), and drone systems revolutionized workplace safety. Computer vision is increasingly critical in enhancing workplace safety through AI-driven applications (Akinsemoyin et al., 2023). It facilitates various functions such as monitoring employee behavior, identifying potential hazards, and providing real-time alerts. A prime example of this technology in action is the deployment of thermal cameras to detect heat stress among workers (Sharma et al., 2022). This allows continuous monitoring of body temperatures, enabling timely interventions like cooling breaks or the provision of suitable PPE. Additionally, computer vision plays a vital role in surveillance, with AI-enhanced cameras tracking employee movements and quickly identifying potential dangers like trip hazards or unsecured machinery (Murugesan et al., 2023). These systems also monitor access to restricted or hazardous areas, bolstering workplace safety (Aslan et al., 2023). The expansion of AI technologies has led to significant transformations in data management, computer vision, and ML. In the dynamic field of DL, numerous challenges related to computer vision such as classification, recognition, language processing, video analysis, gesture detection, and robotics are evolving (Hammoudeh et al., 2022; Morris and Joppa, 2021). Still, the hybridization of computing power with image processing provides very good results (Aslan et al., 2023; Bhana et al., 2023). Similarly, VR has become an essential tool for safety training, particularly in sectors where real-world training poses significant risks. By incorporating VR, employers are able to equip their workforce with the necessary skills and knowledge to navigate hazardous scenarios safely, significantly reducing the potential for workplace injuries and deaths by enhancing risk prevention education (Li et al., 2018). This approach is not only cost-effective and targeted but also pivotal in reducing errors and boosting accident prevention efforts. VR has started to supplant traditional training methods such as PowerPoint presentations and videos by providing a more interactive and memorable learning experience (Gao et al., 2022). Sectors like chemical (Garcia et al., 2021; Kumar et al., 2021), construction (Rokooei et al., 2023; Sacks et al., 2013) and mining (Li et al., 2020; van and Villiers, 2009) have increasingly turned to VR training solutions, attracted by their ability to cut costs and decrease incidents of injuries and fatalities.

Further, the continuous research and development of unmanned aerial vehicles (UAV) has created a new opportunity to improve the workplace environment (Zhou, 2018). Unmanned Aerial Vehicles (UAVs) are increasingly being outfitted with high resolutions camera settings, multiple sensors, and advance communication tools that allow for the rapid transmission of real-time data pertinent to construction activities. These UAVs can perform functions similar to those carried out by manned vehicles, but with greater efficiency and at a lower cost (Zhou, 2018). Significant progress in UAV technology has been made in areas such as battery life, GPS accuracy, navigational skills, and control dependability. These advancements have led to the development of cost-effective and lightweight aerial systems. As a result, there has been a notable increase in the use of UAVs in recent years, becoming more widespread over the past decade (Ham et al., 2016; Peter Liu et al., 2014). The advanced UAVs have potential to inspect hazardous zone with details (Kas and Johnson, 2020; Nooralishahi et al., 2021). This may nullify direct physical human contact with hazardous material and, hence, decrease the chances of injuries and fatalities.

6. Advancements of AI for updating existing policies and regulations in OHS

The inclusion of Artificial Intelligence (AI) in OHS protocols signifies a pivotal change in addressing workplace hazards, especially in sectors with higher risks. AI technology is poised to reshape existing OHS guidelines and regulations towards a more proactive and effective framework. The following are the potential impacts of AI on shaping modern OHS measures. And re-shaping the existing policy:

- Advancing Risk Management and Preventing Incidents: Traditional OHS methods are often reactive, dealing with incidents post-occurrence (Kontogiannis et al., 2017). AI introduces a shift towards a forward-thinking methodology, utilizing predictive analytics and ongoing monitoring to detect and address risks beforehand. AI-enhanced tools like drones and robots can perform risky operations, minimizing human interaction with unsafe conditions (Kas and Johnson, 2020). Such technological shifts require a restructuring of policies to integrate AI's anticipatory abilities, encouraging the use of these innovations for better risk management with OHS advancement.
- Enhanced Real-Time Monitoring and Data Utilization: AI applications with ML and computer vision, enable continuous surveillance using sensors, cameras, and wearable tech (Adem et al., 2020). These devices gather and analyze data concerning the workforce's health, environmental conditions, and imminent dangers continuously. This capability for instantaneous feedback and alerts could drastically lower accident rates at work (Márquez-Sánchez et al., 2021). Traditional approach in OHS regulates workers health and workplace dangers with periodic evaluation only. Therefore, regulations should evolve to require the implementation of AI-based monitoring, ensuring adherence to safety norms and facilitating a rapid response to new hazards.
- Refining Training and Simulation Techniques: AI-powered simulations can significantly improve OHS training by providing realistic and immersive environments where workers can rehearse emergency protocols (Scorgie et al., 2024). This not only bolsters safety but also operational efficiency, enabling personnel to face various potential dangers within a safe setting. Regulations related to training need to be updated to encompass AI simulation standards that meet defined safety and effectiveness benchmarks.
- Developing Legal and Regulatory Support Structures: Incorporating AI within OHS demands comprehensive legal frameworks that support the adoption of such technologies (Jarota, 2023). This involves setting benchmarks for AI system efficacy, dependability, and safety. It is essential for regulatory bodies to collaborate with industry experts to formulate rules that enable the safe and effective application of AI, ensuring compliance with established safety regulations and healthcare security (Palaniappan et al., 2024).

The following **Table 4** represents the major differences of traditional and AI-enhanced OHS policies.

Table 4. Major differences of traditional and AI-enhanced OHS policies.

Area	Traditional OHS Policies	AI-Powered OHS Policies
Risk Management	Reactive, incident-based	Proactive, predictive analytics-based
Monitoring	Periodic inspections	Continuous real-time monitoring
Data Collection	Manual reporting	Automated data collection via sensors, drones, and wearables
Training	Traditional methods (lectures, manuals)	AI-driven simulations and immersive VR training
Incident Response	Post-incident analysis	Preemptive measures and early warnings
Regulatory Compliance	Static compliance checks	Dynamic compliance through real-time data analysis
Worker Involvement	Limited to compliance and reporting	Enhanced engagement with real-time feedback
Data Privacy and Ethics	Basic data protection measures	Comprehensive data privacy and ethical guidelines for AI use
Skill Requirements	Basic safety training	Advanced training in AI tools and technologies
Legal Framework	Established standards and regulations	Evolving standards to include AI capabilities
Cost Implications	High costs due to accidents and non-compliance	Initial high investment, but long-term cost savings through prevention
Decision-Making	Human-based decision-making	AI-assisted decision-making
Flexibility and Adaptability	Rigid and slow to adapt	Flexible, quick to adapt to new data and insights
Worker Health Monitoring	Limited to physical exams	Continuous health monitoring through wearable
Incident Documentation	Manual documentation	Automated documentation and analysis
Preventive Measures	Basic preventive measures	Advanced preventive measures using AI predictions
Hazard Identification	Human assessment	AI-powered hazard identification and analysis

7. Conclusion

The integration of Artificial Intelligence (AI) in Occupational Health and Safety (OHS) across high-risk industries like construction, mining, and oil and gas has notably enhanced risk management strategies traditionally dependent on human judgment and site accessibility. Key AI technologies applied include computer vision for real-time monitoring of worksites, sensor networks for data collection, machine learning for predictive analysis, and knowledge-based systems for decision-making. These technologies streamline the identification and management of hazards from the planning stage through active operations, facilitating a more proactive approach to safety. In the construction sector, AI is integrated with building information modeling to preemptively identify risks during design and planning phases. Similarly, in mining and oil and gas, extensive sensor networks and computer vision systems offer robust frameworks for hazard detection, risk assessment, and sometimes, prediction of potential safety incidents. AI's role in personalizing training protocols also underscores its importance in enhancing worker preparedness and response strategies.

Despite these advancements, the application of AI in OHS is not without challenges. Key barriers include the high cost of AI implementation, which may be prohibitive for small and medium-sized enterprises; a lack of skilled workforce trained in AI technologies; and the ethical, legal, and social concerns related to data privacy, worker surveillance, and algorithmic bias. These issues complicate the integration of AI into existing OHS frameworks and may also introduce new risks such as cyber threats and psychosocial stress due to human-machine interactions. To overcome these barriers and fully harness the potential of AI in enhancing workplace safety, there is a pressing need for multidisciplinary research and collaboration. This should be aimed at developing cost-effective AI solutions, fostering an AI-savvy workforce, and establishing robust regulatory frameworks that address ethical and legal concerns while promoting OHS equity and governance. Further, exploring the development of digital twins and enhancing IoT infrastructure could significantly improve real-time data transmission and monitoring, leading to more dynamic and responsive OHS practices.

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