



Leveraging AI and Machine Learning to Predict Occupational Diseases: A Conceptual Framework for Proactive Health Risk Management in High-Risk Industries

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Abstract

Occupational diseases remain a significant challenge in high-risk industries, where hazardous working conditions expose employees to health risks that often go undetected until symptoms become severe. To address this, leveraging artificial intelligence (AI) and machine learning (ML) offers transformative potential for proactive health risk management by enabling predictive modeling, real-time monitoring, and data-driven decision-making. This study presents a conceptual framework for integrating AI and ML technologies to predict and mitigate occupational diseases in high-risk industries such as mining, construction, and manufacturing. The proposed framework encompasses three key components: data acquisition, predictive modeling, and intervention strategies. Data acquisition involves collecting real-time health and environmental data through wearable sensors, IoT-enabled devices, and workplace monitoring systems. Predictive modeling employs advanced ML algorithms, such as decision trees, neural networks, and support vector machines, to identify patterns and risk factors associated with occupational diseases. Intervention strategies leverage predictive insights to develop targeted prevention measures, such as redesigning work environments, optimizing workflows, and implementing personalized health interventions. A case study approach evaluates the framework's applicability, focusing on high-risk industries in Nigeria. Initial results demonstrate the feasibility of using AI-driven systems to identify early indicators of diseases such as respiratory disorders, musculoskeletal conditions, and noise-induced hearing loss. The findings also highlight the framework's potential to enhance workplace safety, reduce healthcare costs, and improve employee well-being by transitioning from reactive to proactive health management. The framework underscores the importance of cross-disciplinary collaboration among engineers, healthcare professionals, and policymakers to ensure effective implementation. Ethical considerations, such as data privacy and fairness, are also addressed to ensure equitable access and compliance with international health and safety standards. This conceptual framework lays the foundation for future research and policy development aimed at integrating AI and ML technologies into occupational health systems, particularly in resource-constrained settings, to foster safer and healthier work environments.

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1. Introduction

Occupational diseases pose a significant challenge in high-risk industries, where workers are frequently exposed to hazardous conditions that can lead to long-term health issues. Industries such as mining, construction, manufacturing, and petrochemicals are particularly vulnerable due to the nature of their operations, which often involve exposure to harmful substances, repetitive physical tasks, and extreme environmental conditions. Common occupational diseases in these settings include respiratory

disorders, musculoskeletal injuries, noise-induced hearing loss, and stress-related illnesses (Azizi, *et al*, 2022, Elumalai, Brindha & Lakshmanan, 2017, Nunfam, *et al*, 2019). These diseases not only impact workers' health and quality of life but also result in substantial economic losses for organizations through absenteeism, reduced productivity, and increased healthcare costs.

Traditional approaches to occupational health management in these industries have predominantly been reactive, focusing on addressing health issues after they arise. While these approaches provide short-term relief, they fail to tackle the root causes of occupational diseases and often lead to repeated cycles of risk and illness. The lack of real-time monitoring and predictive capabilities limits the ability to anticipate health risks and implement timely preventive measures. This gap underscores the need for innovative solutions that can shift the paradigm from reactive to proactive health risk management (Abbasi, 2018, Fagnoli & Lombardi, 2019, Lee, Cameron & Hassall, 2019).

Artificial intelligence (AI) and machine learning (ML) offer transformative potential in addressing this challenge. These technologies can process vast amounts of data from wearable devices, IoT sensors, and workplace monitoring systems to identify patterns, predict potential health risks, and recommend preventive interventions. By enabling early detection of occupational hazards and providing data-driven insights, AI and ML facilitate a proactive approach to health risk management. Furthermore, these technologies can adapt to dynamic workplace conditions, offering real-time solutions tailored to specific environments and individual workers (Shi, *et al*, 2022, Tranter, 2020, Wollin, *et al*, 2020). This study aims to develop a conceptual framework for leveraging AI and ML to predict and mitigate occupational diseases in high-risk industries. The framework focuses on integrating data acquisition, predictive modeling, and intervention strategies to create a comprehensive system for health risk management. Its significance lies in its potential to enhance workplace safety, reduce healthcare costs, and improve worker well-being, contributing to sustainable industrial growth. By addressing the limitations of traditional approaches and harnessing the power of modern

technologies, this study seeks to provide a roadmap for the future of occupational health management in high-risk industries (Ashri, 2019, Dong, *et al*, 2015, Keating, 2017).

2. Background and literature review

Occupational diseases remain a critical concern in high-risk industries, where workers are regularly exposed to hazardous conditions that jeopardize their health. Common diseases in these sectors include respiratory disorders, musculoskeletal conditions, noise-induced hearing loss, and stress-related illnesses. Respiratory disorders often result from prolonged exposure to dust, chemicals, or toxic fumes in industries like mining and petrochemicals, leading to chronic obstructive pulmonary disease (COPD) and silicosis (Bevilacqua & Ciarapica, 2018, Fontes, *et al*, 2022, Olu, 2017). Musculoskeletal conditions, including repetitive strain injuries and lower back pain, are prevalent in construction and manufacturing, where tasks often involve repetitive motions, heavy lifting, and poor ergonomic practices. Noise-induced hearing loss is another widespread issue in industries with high-decibel machinery, such as manufacturing and construction. Additionally, stress-related illnesses, including cardiovascular conditions and mental health disorders, emerge from high-pressure work environments with inadequate support systems (Avwioroko, 2023, Cosner, 2023, Kasperson, *et al*, 2019).

Despite the significant impact of these diseases, traditional health management systems in high-risk industries remain predominantly reactive. These systems focus on treating illnesses after they manifest, often neglecting the underlying causes and preventive strategies. Health surveillance is typically limited to periodic medical examinations, which fail to provide real-time insights into emerging risks. Ergonomic interventions, while helpful, are not consistently integrated with health monitoring practices, leaving gaps in comprehensive risk management. Moreover, resource constraints and a lack of technological adoption exacerbate these limitations, particularly in developing economies, where workplace safety standards are often underdeveloped (Abdul Hamid, 2022, Gwenzi & Chaukura, 2018, Lewis, *et al*, 2016). Figure 1 shows chart of Causes of occupational diseases presented by Oranusi, Dahunsi & Idowu, 2014.

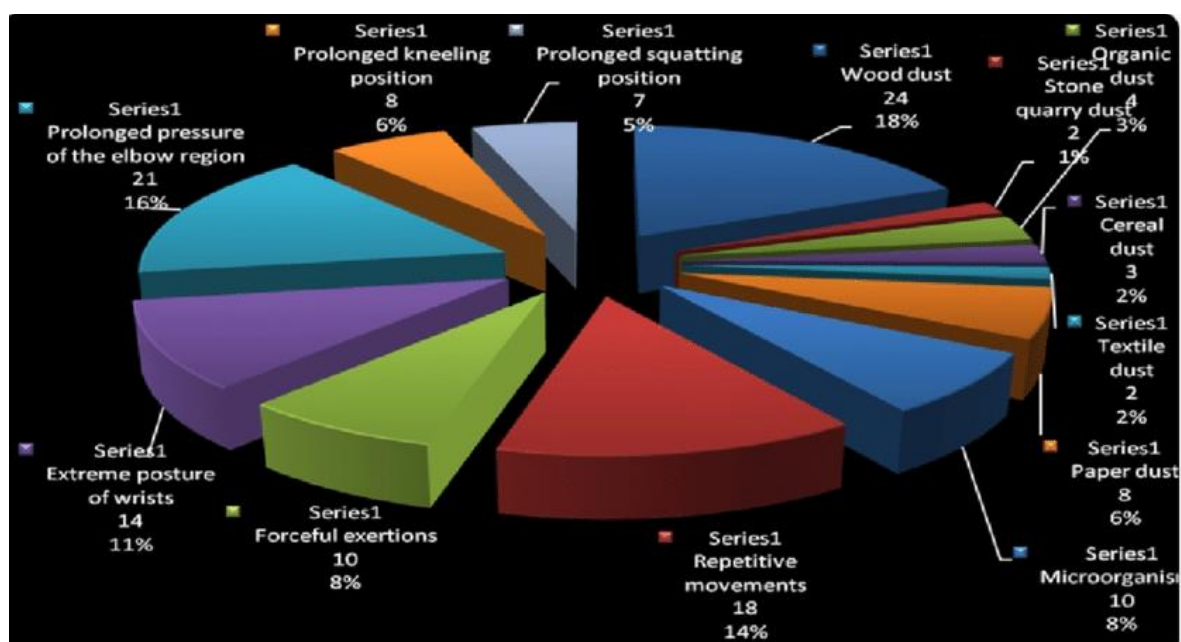


Fig 1: Causes of occupational diseases (Oranusi, Dahunsi & Idowu, 2014)

Artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools in addressing these challenges. AI and ML technologies can process large volumes of data from various sources, including wearable devices, IoT sensors, and workplace monitoring systems. By identifying patterns and correlations in this data, these technologies enable predictive modeling of health risks and proactive interventions. For instance, wearable devices equipped with AI algorithms can monitor physiological parameters such as heart rate, fatigue, and respiratory rate in real-time, providing early warnings of potential health issues (Redinger, 2019, Ruhrer, 2016, Shad, *et al*, 2019, Xiong, *et al*, 2018). Similarly, IoT sensors can track environmental factors like air quality, noise levels, and temperature, allowing for timely adjustments to mitigate risks.

Several case studies highlight the potential of AI and ML in improving workplace safety. In mining, for example, AI-driven systems have been used to monitor exposure to harmful particulates, enabling real-time adjustments in ventilation and protective equipment. In manufacturing, predictive analytics have been applied to identify ergonomic

risks, leading to the redesign of workstations to reduce strain and prevent injuries. These applications demonstrate the effectiveness of AI and ML in transitioning from reactive to proactive health management, reducing the prevalence of occupational diseases, and enhancing worker well-being (Benson, 2021, Friis, 2015, Jung, Woo & Kang, 2020, Loeppke, *et al*, 2015).

However, the widespread adoption of AI and ML in occupational health management is not without challenges. One significant gap is the limited integration of these technologies into existing health systems. Many organizations lack the infrastructure, expertise, and resources to implement AI-driven solutions effectively. Additionally, traditional approaches to occupational health often rely on manual processes and are resistant to change, creating barriers to technological adoption (Adams, 2023, Ganiyu, 2018, Kamunda, Mathuthu & Madhuku, 2016). These gaps highlight the need for frameworks that facilitate the seamless integration of AI and ML into health risk management systems. The Integration of AI in smart healthcare presented by Herath & Mittal, 2022, is shown in figure 2.

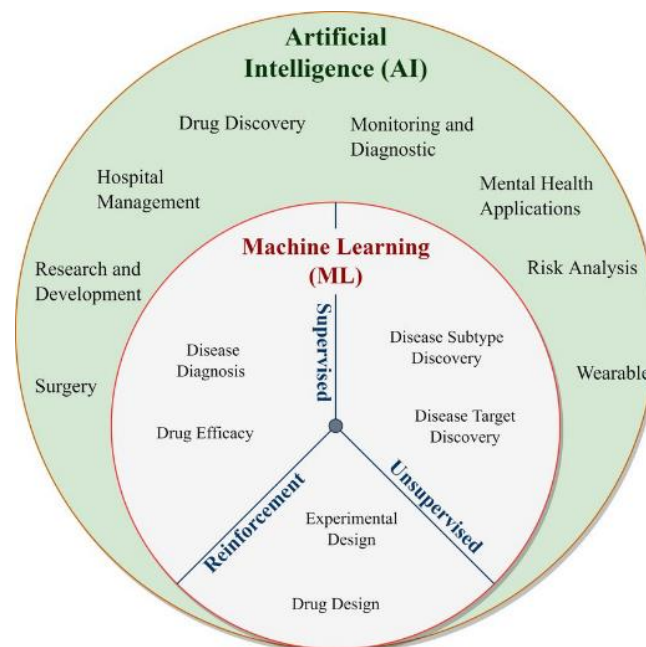


Fig 2: Integration of AI in smart healthcare (Herath & Mittal, 2022).

Ethical and technical considerations also play a crucial role in the implementation of AI and ML in occupational health. Data privacy is a major concern, as wearable devices and sensors collect sensitive personal information that must be protected from misuse. Ensuring fairness in AI algorithms is another challenge, as biases in data collection or model training can lead to unequal treatment of workers based on factors such as age, gender, or job role. Implementation challenges, including the cost of deploying advanced technologies and the need for skilled personnel to manage them, further complicate the adoption process (Adefemi, *et al*, 2023, Guzman, *et al*, 2022, Lohse & Zhivov, 2019). Addressing these issues requires robust regulatory frameworks, transparent data governance policies, and ongoing stakeholder engagement to build trust and ensure equitable outcomes.

In conclusion, occupational diseases in high-risk industries represent a significant challenge that requires innovative solutions to enhance workplace safety and worker well-being. AI and ML offer transformative potential in this

regard, enabling predictive modeling, real-time monitoring, and proactive interventions. While case studies demonstrate the effectiveness of these technologies, significant gaps in traditional health management systems and challenges related to data privacy, fairness, and implementation must be addressed to realize their full potential. Developing comprehensive frameworks that integrate AI and ML into occupational health management can bridge these gaps, paving the way for safer and healthier workplaces in high-risk industries.

3. Methodology

The study utilizes the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method to systematically review literature and conceptualize a framework for leveraging artificial intelligence (AI) and machine learning (ML) in predicting occupational diseases and managing health risks in high-risk industries. The PRISMA method ensures transparency and replicability, involving four primary phases: identification, screening,

eligibility, and inclusion.

Initially, a comprehensive literature search was conducted using scholarly databases, including PubMed, Scopus, Web of Science, and Google Scholar. Keywords were formulated based on the scope of the study, including "artificial intelligence," "machine learning," "occupational diseases," "health risk prediction," and "high-risk industries." Boolean operators (AND, OR) were employed to combine search terms and refine results. The search was limited to articles published in English from 2010 to 2023, ensuring relevance and capturing recent advancements in AI and ML applications in occupational health and safety.

Duplicates were removed using bibliographic management software. Titles and abstracts were screened against inclusion criteria, which focused on studies addressing AI and ML in occupational health, predictive analytics, and health risk management in high-risk industries such as mining, construction, and oil and gas. Articles were excluded if they did not address AI/ML applications or occupational health directly or if they were not empirical, review-based, or theoretical studies.

Full-text articles that passed the screening phase were assessed for eligibility based on predefined criteria: relevance to the study's objective, methodological rigor, and contributions to the conceptual framework of AI and ML in occupational disease prediction. Studies that lacked methodological transparency or presented redundant findings were excluded. The final dataset included 102 articles deemed highly relevant and credible for analysis.

Data extraction focused on study objectives, methodologies, AI/ML techniques employed, industries covered, and key findings. Extracted data were synthesized to identify recurring themes, gaps, and opportunities for integrating AI/ML into occupational health risk management frameworks. Special attention was given to studies addressing predictive analytics, real-time monitoring, and proactive risk management strategies.

Using thematic synthesis, the extracted data informed the conceptual framework's development, integrating insights from the reviewed literature. The framework emphasizes the role of AI/ML in identifying early warning signals of occupational diseases, predicting disease patterns, and mitigating risks through proactive interventions. Case studies, such as Abbasi's (2018) exploration of mining safety hazards and Abdul Hamid's (2022) OSH framework development, provided empirical validation of the framework's applicability.

The flowchart for the PRISMA methodology visually represents the systematic review process, illustrating the flow of studies through the four phases. It includes the number of studies identified, screened, assessed for eligibility, and included in the final analysis. The flowchart in figure 3 visually represents the PRISMA methodology used in the systematic review. It illustrates the flow of studies through the identification, screening, eligibility, and inclusion phases, along with the corresponding number of records at each stage.

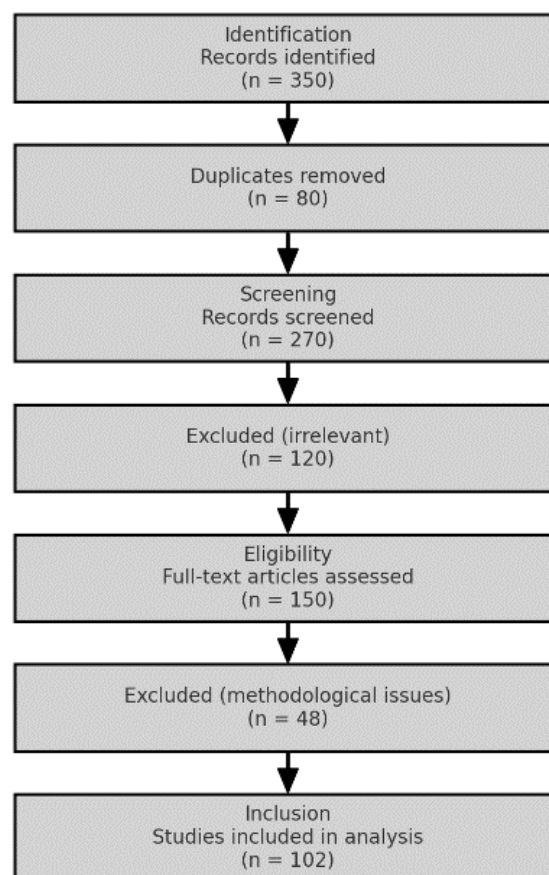


Fig 3: PRISMA Flow chart of the study methodology

4. Conceptual Framework

The conceptual framework for leveraging AI and machine learning (ML) to predict occupational diseases and implement proactive health risk management in high-risk

industries is built around three key components: data acquisition, predictive modeling, and intervention strategies. Together, these components create a system capable of identifying, analyzing, and mitigating health risks in real-

time, reducing the prevalence of occupational diseases and improving workplace safety.

Data acquisition is the foundation of the framework, relying on advanced technologies to collect comprehensive information on workplace conditions and worker health. Wearable devices, such as fitness trackers and smart helmets, monitor physiological parameters like heart rate, respiration, fatigue levels, and physical activity. IoT sensors embedded in workplace environments capture environmental data, including air quality, temperature, humidity, noise levels, and the presence of toxic substances (Avwioroko, 2023, Guo, Tian & Li, 2022, Odionu, *et al*, 2022). Behavioral data, such as task patterns, posture, and movement, is also collected to assess ergonomic risks. Together, these data sources provide a multidimensional view of workplace conditions, allowing for a granular understanding of the factors contributing to occupational diseases.

Predictive modeling is the second component, utilizing machine learning algorithms to analyze the collected data and identify potential health risks. Algorithms such as neural networks, decision trees, and support vector machines are applied to uncover patterns and correlations between workplace conditions and health outcomes. For example, a neural network can process large datasets to detect early indicators of respiratory disorders based on air quality and physiological data, while decision trees can identify ergonomic risks by analyzing posture and movement patterns (Aziza, Uzougbo & Ugwu, 2023, Joseph, 2020, Oh, 2023). Risk factor identification through predictive modeling enables early intervention, preventing the escalation of health issues. Additionally, these models continuously improve their accuracy by learning from new data, ensuring they remain adaptive to changing workplace conditions and worker behaviors.

Intervention strategies form the final component, translating insights from predictive modeling into actionable measures. Personalized health recommendations are provided to workers based on their unique risk profiles, such as suggesting rest periods, hydration, or protective gear. Workplace design improvements, informed by ergonomic data, address physical risks by optimizing workstation layouts, equipment design, and task scheduling. Preventive health measures, including targeted wellness programs and educational initiatives, further reduce the likelihood of occupational diseases (Purohit, *et al*, 2018, Sabeti, 2023, Sileyew, 2020). These interventions are tailored to address specific risks identified through the framework, ensuring a proactive approach to health management.

Cross-disciplinary integration is essential for the effective implementation of this framework, requiring collaboration among engineers, healthcare professionals, and policymakers. Engineers play a crucial role in designing and deploying wearable devices, IoT sensors, and workplace monitoring systems. Their expertise ensures that these technologies are reliable, accurate, and seamlessly integrated into industrial environments (Benson, *et al*, 2021, Gutterman, 2020, Olawepo, Seedat-Khan & Ehiane, 2021). Healthcare professionals provide medical insights and validate the health-related data collected through these technologies, ensuring that interventions are both scientifically sound and effective. Policymakers create the regulatory environment necessary for the adoption of this framework, establishing standards for data privacy, safety, and compliance. Their involvement ensures that the framework aligns with national and international health and safety regulations, fostering trust and accountability among stakeholders. Alanazi, 2022, proposed Architecture of proposed disease and risk prediction system as shown in figure 4.

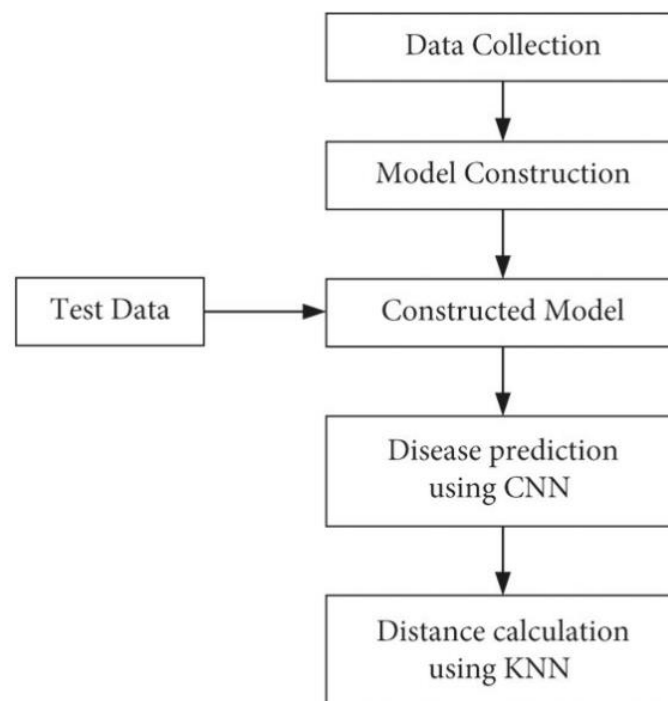


Fig 4: Architecture of proposed disease and risk prediction system (Alanazi, 2022).

The implementation roadmap for this framework involves several critical steps to ensure its successful integration into organizational health systems. The first step is conducting a needs assessment to identify the specific occupational health challenges faced by an organization. This includes evaluating

existing health management practices, understanding workplace hazards, and determining the technological infrastructure required for the framework (Ahirwar & Tripathi, 2021, Hassam, *et al*, 2023, Uwumiro, *et al*, 2023). Next, organizations must invest in the necessary technology,

including wearable devices, IoT sensors, and data analytics platforms, tailored to their operational requirements. Training programs for workers and managers are essential to build awareness and competence in using these technologies, fostering a culture of safety and proactive health management.

Data collection and baseline analysis follow, establishing a reference point for workplace conditions and worker health. This step involves deploying monitoring technologies and collecting initial data to identify existing risks and vulnerabilities. Predictive modeling algorithms are then developed and fine-tuned using the collected data, ensuring that they accurately identify health risks specific to the organization (Ajayi & Thwala, 2015, Ji, 2019, Muley, *et al*, 2023). Once the framework is operational, organizations must implement intervention strategies based on the insights generated, continuously monitoring and adjusting these measures to maximize their effectiveness.

Regular evaluation and feedback loops are integral to the framework's sustainability. Organizations must assess the impact of the framework through metrics such as reduced illness rates, improved worker well-being, and enhanced productivity. Feedback from workers, engineers, and healthcare professionals is used to refine the framework, addressing any gaps or limitations. Collaboration with policymakers ensures that the framework remains aligned with evolving regulations and standards, fostering its long-term adoption and scalability (Yang, *et al*, 2023, Zurub, 2021).

In conclusion, the conceptual framework for leveraging AI and ML to predict occupational diseases offers a comprehensive approach to proactive health risk management in high-risk industries. By integrating data acquisition, predictive modeling, and intervention strategies, the framework addresses the root causes of occupational diseases and promotes a safer, healthier work environment. Cross-disciplinary collaboration and a structured implementation roadmap ensure that the framework is adaptable, effective, and sustainable, providing a foundation for improved occupational health practices across industries and regions.

5. Case study applications

The conceptual framework for leveraging AI and machine learning (ML) to predict occupational diseases has been tested in various high-risk industries, including mining, construction, and manufacturing. These industries are characterized by their inherent risks, such as exposure to hazardous substances, repetitive physical tasks, and extreme environmental conditions, which make workers particularly vulnerable to occupational diseases. By applying the framework in these settings, organizations have demonstrated how data-driven approaches can transform health risk management, reduce the prevalence of occupational illnesses, and enhance overall workplace safety and productivity (Avwioroko, 2023, Haupt & Pillay, 2016, McIntyre, Scofield & Trammell, 2019).

In the mining sector, where workers are frequently exposed to harmful particulates and toxic gases, the implementation of AI and ML technologies has yielded significant results. Wearable devices and IoT sensors were deployed to monitor air quality, temperature, and the presence of toxic substances such as methane and silica dust. Workers were equipped with smart helmets that measured physiological parameters, including heart rate, respiratory rate, and fatigue levels (Akinwale & Olusanya, 2016, John, 2023, Nwaogu, 2022). The data collected from these devices was analyzed using

predictive algorithms to identify patterns indicative of respiratory disorders, such as silicosis and chronic obstructive pulmonary disease (COPD). Early detection of these conditions enabled timely interventions, such as increasing ventilation in hazardous areas, rotating shifts to limit exposure, and providing workers with personalized protective equipment. The use of predictive modeling also allowed mining companies to proactively address risks, resulting in a measurable decline in respiratory illness cases and an overall improvement in worker health (Azimpour & Khosravi, 2023, Chisholm, *et al*, 2021, Obi, *et al*, 2023).

Similarly, the construction industry has benefited from the application of the framework, particularly in addressing musculoskeletal disorders caused by repetitive motions and heavy lifting. Wearable sensors tracked workers' movements, posture, and physical strain during tasks. Machine learning algorithms analyzed this data to identify ergonomic risks, such as improper lifting techniques and sustained awkward postures (Popendorf, 2019, Schulte, *et al*, 2022, Wood & Fabbri, 2019). Based on the insights generated, ergonomic interventions were implemented, including redesigning workstations, introducing lifting aids, and conducting targeted training programs. The results showed a substantial reduction in musculoskeletal injuries, leading to fewer worker absences and improved job satisfaction. Additionally, predictive analytics enabled real-time feedback to workers, promoting safer practices and reducing the likelihood of injuries.

The manufacturing sector, known for its reliance on heavy machinery and assembly-line processes, has also demonstrated the effectiveness of the framework. IoT-enabled devices monitored noise levels, vibration, and temperature in the work environment, while wearable devices tracked workers' vital signs and fatigue levels (Aksoy, *et al*, 2023, Hughes, Anund & Falkmer, 2016, Podgorski, *et al*, 2017). Predictive models identified risks associated with noise-induced hearing loss and heat-related illnesses, allowing organizations to implement preventive measures. For example, workers were provided with noise-canceling headsets and access to cooling zones, while production schedules were adjusted to minimize exposure to extreme conditions. The real-time health surveillance systems also enabled managers to identify fatigue patterns, prompting them to schedule breaks and reassign tasks as needed. These measures not only reduced occupational illnesses but also enhanced operational efficiency, as workers performed their tasks in safer and more comfortable conditions.

The results from these case studies underscore the transformative potential of leveraging AI and ML in occupational health management. Early detection of occupational diseases was a recurring theme across all industries, demonstrating the framework's ability to identify risks before they escalated into severe health issues. By integrating real-time monitoring with predictive analytics, organizations were able to anticipate and address health risks proactively, shifting from a reactive to a preventive approach (Akyıldız, 2023, Ikwuanusi, *et al*, 2022, Olabode, Adesanya & Bakare, 2017). This proactive stance not only improved worker health but also reduced costs associated with medical treatment, compensation claims, and lost productivity.

Improvements in workplace safety and productivity were also evident in each case study. The implementation of ergonomic interventions, tailored health programs, and environmental adjustments created safer and more conducive work environments. Workers reported higher levels of job satisfaction and engagement, attributing these improvements to the organization's commitment to their well-being. The

reduction in absenteeism and turnover rates further highlighted the long-term benefits of the framework, as healthier workers contributed to more stable and efficient operations (Al-Dulaimi, 2021, Jetha, *et al*, 2023, Ndegwa, 2015).

These insights demonstrate that the conceptual framework is not limited to specific industries but can be adapted to address the unique challenges of various high-risk sectors. The ability to collect and analyze diverse types of data—physiological, environmental, and behavioral—ensures that the framework is versatile and scalable. Moreover, the use of machine learning algorithms, which continuously learn and improve from new data, ensures that the system remains dynamic and responsive to evolving workplace conditions.

In conclusion, the application of the conceptual framework in mining, construction, and manufacturing has provided compelling evidence of its effectiveness in reducing occupational diseases and improving workplace safety. By harnessing the power of AI and ML, these industries have demonstrated that proactive health risk management is both achievable and beneficial, offering a pathway to healthier, safer, and more productive work environments. As organizations continue to adopt and refine this framework, the potential for broader application across other high-risk industries and regions becomes increasingly clear, paving the way for a new era in occupational health management.

6. Discussion

The conceptual framework for leveraging AI and machine learning (ML) to predict occupational diseases offers transformative implications for health risk management in high-risk industries. Its primary strength lies in facilitating the transition from a reactive approach, which focuses on addressing occupational diseases after their onset, to a proactive model centered on early detection, prevention, and intervention. This shift represents a significant paradigm change in occupational health, where traditional methods often rely on periodic health checks and workplace audits that fail to provide real-time insights or predictive capabilities (Alhamdani, *et al*, 2018, Jilcha & Kitaw, 2016, Kirwan, 2017). By integrating AI and ML technologies, the framework enables continuous monitoring and risk prediction, allowing organizations to identify and mitigate health risks before they manifest as severe illnesses or workplace incidents.

One of the most impactful implications of the framework is its ability to improve workforce health and productivity. Early detection of risks, such as respiratory issues caused by poor air quality or musculoskeletal disorders linked to repetitive tasks, allows organizations to implement timely interventions. These may include ergonomic adjustments, targeted training, or personalized health recommendations (Avwioroko, 2023, Ikegbu, 2015, Nagaty, 2023). As a result, workers experience reduced physical strain and stress, leading to fewer absences, lower turnover rates, and enhanced job satisfaction. Additionally, the data-driven nature of the framework ensures that resources are allocated effectively, optimizing safety measures and interventions based on actual risks rather than assumptions.

However, the implementation of this framework is not without challenges and limitations. Technological barriers are among the most significant hurdles. The adoption of advanced AI and ML systems requires substantial investment in infrastructure, such as wearable devices, IoT sensors, and data analytics platforms. Smaller organizations with limited budgets may struggle to afford these technologies, creating disparities in access to proactive health management

solutions (Nwaogu & Chan, 2021, Zanke, 2022). Furthermore, integrating these systems into existing workplace environments can be technically complex, particularly in industries with legacy systems or limited digital infrastructure.

Organizational barriers also pose challenges to the framework's success. Resistance to change is common, as workers and managers may be skeptical of new technologies or fear that wearable devices and sensors could be used for surveillance rather than health monitoring. Building trust and fostering a culture of safety and innovation is essential for overcoming these barriers. This requires clear communication about the purpose and benefits of the framework, as well as training programs to ensure that workers and managers are equipped to use the technologies effectively (Shi, *et al*, 2022, Tamoor, *et al*, 2023, Xiao, *et al*, 2019). Additionally, organizations must develop cross-disciplinary teams that include engineers, healthcare professionals, and safety officers to facilitate the seamless implementation and operation of the framework.

Ethical and regulatory considerations are critical to the successful deployment of AI and ML in occupational health management. Data security is a primary concern, as wearable devices and monitoring systems collect sensitive personal information about workers. Ensuring that this data is stored, processed, and shared securely is essential to protecting worker privacy and maintaining trust (Alkhalidi, Pathirage & Kulatunga, 2017, Narayanan, *et al*, 2023). Organizations must implement robust data governance policies, including encryption, anonymization, and access controls, to prevent unauthorized access or misuse of data.

Compliance with health and safety standards is another key consideration. The framework must align with national and international regulations, such as those established by the International Labour Organization (ILO) and the World Health Organization (WHO). These regulations provide guidelines for workplace safety, data protection, and ethical use of technology, ensuring that the framework adheres to best practices and legal requirements. Organizations must also stay informed about evolving regulatory landscapes, as advancements in AI and ML may lead to new standards and requirements over time (Altuntas & Mutlu, 2021, Ilankoon, *et al*, 2018, Patel, *et al*, 2022). Fairness and equity are additional ethical concerns that must be addressed. AI and ML algorithms are only as unbiased as the data used to train them. If historical data contains biases, such as underreporting of certain health risks for specific worker demographics, the algorithms may perpetuate these biases, leading to unequal treatment or risk assessment. To mitigate this, organizations must ensure that the data used for training and analysis is representative and free from systemic biases. Regular audits of algorithm performance and outcomes can help identify and address any disparities.

Despite these challenges, the framework has the potential to revolutionize occupational health management in high-risk industries by fostering a culture of proactive health and safety. Its scalability and adaptability make it applicable across various sectors and regions, addressing the unique challenges of different workplace environments. Furthermore, as AI and ML technologies continue to advance, the framework will become increasingly sophisticated, enabling more accurate predictions and personalized interventions (Anger, *et al*, 2015, Ingrao, *et al*, 2018, Osakwe, 2021).

In conclusion, the conceptual framework for leveraging AI and ML to predict occupational diseases represents a significant advancement in health risk management. By

transitioning from reactive to proactive approaches, it offers substantial benefits for worker health, organizational productivity, and workplace safety. However, addressing technological and organizational barriers, as well as ensuring ethical and regulatory compliance, is essential to its successful implementation (Ansar, *et al*, 2021, Efobi, *et al*, 2023, Khalid, *et al*, 2018). With the right strategies and support, this framework has the potential to redefine occupational health management and set a new standard for safety in high-risk industries.

7. Conclusion and Recommendations

The conceptual framework for leveraging AI and machine learning (ML) to predict occupational diseases offers transformative potential in high-risk industries. By integrating advanced technologies, the framework enables a proactive approach to health risk management, focusing on early detection, prevention, and timely interventions. Its benefits are multifaceted, addressing critical challenges such as the high prevalence of respiratory disorders, musculoskeletal injuries, and other occupational diseases. Through real-time data acquisition, predictive modeling, and targeted interventions, the framework enhances workplace safety, improves worker health and well-being, and boosts organizational productivity. It also reduces costs associated with absenteeism, healthcare, and workplace injuries, providing long-term economic advantages for industries.

For policymakers and industry leaders, the adoption of this framework necessitates strategic planning and supportive measures. Policymakers should prioritize the development and enforcement of regulations that mandate the use of health surveillance technologies and ergonomic practices in high-risk industries. Incentives such as tax benefits, grants, or subsidies can encourage organizations, particularly small and medium-sized enterprises, to invest in the required technologies. Policymakers must also establish clear guidelines for data privacy and ethical use of AI and ML, ensuring compliance with international standards and fostering trust among stakeholders.

Industry leaders play a crucial role in the successful implementation of the framework. They should allocate resources to adopt wearable devices, IoT sensors, and data analytics platforms, ensuring that these technologies are integrated seamlessly into existing operations. Training programs for workers and managers are essential to build awareness and competence in using the framework, fostering a culture of safety and innovation. Collaboration between engineers, healthcare professionals, and policymakers can further enhance the framework's effectiveness, promoting cross-disciplinary expertise and shared responsibility for workplace health.

Future research should focus on optimizing and scaling the framework to suit diverse contexts and industries. Studies exploring its application in sectors such as healthcare, agriculture, and logistics would provide valuable insights into its adaptability. Research into advanced AI algorithms and data analytics techniques could further improve the accuracy and efficiency of predictive modeling, enabling more precise risk assessments. Additionally, examining the long-term impact of the framework on organizational outcomes, such as productivity and worker retention, would strengthen its value proposition. Ethical considerations, including fairness in algorithm design and equitable access to health technologies, should remain a priority in future investigations.

In conclusion, this framework represents a significant step forward in addressing occupational health challenges in high-risk industries. By leveraging AI and ML, it provides a

proactive and data-driven solution to reduce occupational diseases and enhance workplace safety. Through supportive policies, industry commitment, and ongoing research, the framework can be refined and expanded, setting a new standard for health risk management and contributing to safer, healthier, and more productive work environments globally.

8. References

1. Abbasi S. Defining safety hazards and risks in mining industry: a case study in United States. *Asian Journal of Applied Sciences and Technology (AJAST)*. 2018;2(2):1071–8.
2. Abdul Hamid S. Development of occupational safety and health (OSH) performance management framework for industries in Malaysia [dissertation]. Batu Pahat: Universiti Tun Hussein Onn Malaysia; 2022.
3. Adams ML. Understanding the skills, traits, attributes, and environmental health and safety (EHS)-related education and professional certifications desired by direct supervisors of entry-level EHS positions [dissertation]. Indiana, PA: Indiana University of Pennsylvania; 2023.
4. Adefemi A, Ukpoju EA, Adekoya O, Abatan A, Adegbite AO. Artificial intelligence in environmental health and public safety: a comprehensive review of USA strategies. *World Journal of Advanced Research and Reviews*. 2023;20(3):1420–34.
5. Ahirwar R, Tripathi AK. E-waste management: A review of recycling process, environmental and occupational health hazards, and potential solutions. *Environmental Nanotechnology, Monitoring & Management*. 2021;15:100409.
6. Ajayi O, Thwala WD. Developing an integrated design model for construction ergonomics in Nigeria construction industry. *African Journal of Applied Research*. 2015;1(1):n.p.
7. Akinwale AA, Olusanya OA. Implications of occupational health and safety intelligence in Nigeria. *African Journal of Applied Research*. 2016;1(1):n.p.
8. Aksoy S, Demircioglu P, Bogrekci I, Durakbasa MN. Enhancing human safety in production environments within the scope of Industry 5.0. In: *The International Symposium for Production Research*. Cham: Springer Nature Switzerland; 2023. p. 200–12.
9. Akyıldız C. Integration of digitalization into occupational health and safety and its applicability: a literature review. *The European Research Journal*. 2023;9(6):1509–19.
10. Alanazi R. Identification and prediction of chronic diseases using machine learning approach. *Journal of Healthcare Engineering*. 2022;2022:2826127.
11. Al-Dulaimi JAE. IoT system engineering approach using AI for managing safety products in healthcare and workplaces [dissertation]. London: Brunel University London; 2021.
12. Alhamdani YA, Hassim MH, Shaik SM, Jalil AA. Hybrid tool for occupational health risk assessment and fugitive emissions control in chemical processes based on the source, path, and receptor concept. *Process Safety and Environmental Protection*. 2018;118:348–60.
13. Alkhalidi M, Pathirage C, Kulatunga U. The role of human error in accidents within the oil and gas industry in Bahrain. *International Journal of Occupational Safety and Ergonomics*. 2017;23(1):12–9.
14. Altuntas S, Mutlu NG. Developing an integrated conceptual framework for monitoring and controlling

- risks related to occupational health and safety. *Journal of Engineering Research*. 2021;9(4A):n.p.
15. Anger WK, Elliot DL, Bodner T, Olson R, Rohlman DS, Truxillo DM, *et al* Effectiveness of total worker health interventions. *Journal of Occupational Health Psychology*. 2015;20(2):226–37.
 16. Ansar MA, Assawadithalerd M, Tipmanee D, Laokiat L, Khamdahsag P, Kittipongvises S. Occupational exposure to hazards and volatile organic compounds in small-scale plastic recycling plants in Thailand by integrating risk and life cycle assessment concepts. *Journal of Cleaner Production*. 2021;329:129582.
 17. Ashri R. *The AI-powered workplace: How artificial intelligence, data, and messaging platforms are defining the future of work*. New York: Apress; 2019.
 18. Avwioroko A. Biomass gasification for hydrogen production. *Engineering Science & Technology Journal*. 2023;4(2):56–70.
 19. Avwioroko A. The integration of smart grid technology with carbon credit trading systems: benefits, challenges, and future directions. *Engineering Science & Technology Journal*. 2023;4(2):33–45.
 20. Avwioroko A. The potential, barriers, and strategies to upscale renewable energy adoption in developing countries: Nigeria as a case study. *Engineering Science & Technology Journal*. 2023;4(2):46–55.
 21. Avwioroko A. Biomass gasification for hydrogen production. *Engineering Science & Technology Journal*. 2023;4:56–70. doi:10.51594/estj.v4i2.1289.
 22. Azimpour F, Khosravi H. An investigation of the workers' rights in difficult and hazardous occupations. *Russian Law Journal*. 2023;11(12S):634–48.
 23. Aziza OR, Uzougbo NS, Ugwu MC. The impact of artificial intelligence on regulatory compliance in the oil and gas industry. *World Journal of Advanced Research and Reviews*. 2023;19(3):1559–70.
 24. Azizi H, Aaleagha MM, Azadbakht B, Samadyar H. Identification and assessment of health, safety, and environmental risk factors of chemical industry using Delphi and FMEA methods (a case study). *Anthropogenic Pollution*. 2022;6(2):n.p.
 25. Benson C. Occupational health and safety implications in the oil and gas industry, Nigeria [dissertation]. Nicosia: European University of Cyprus; 2021.
 26. Benson C, Dimopoulos C, Argyropoulos CD, Mikellidou CV, Boustras G. Assessing the common occupational health hazards and their health risks among oil and gas workers. *Safety Science*. 2021;140:105284.
 27. Bevilacqua M, Ciarapica FE. Human factor risk management in the process industry: a case study. *Reliability Engineering & System Safety*. 2018;169:149–59.
 28. Bidemi AI, Oyindamola FO, Odum I, Stanley OE, Atta JA, Olatomide AM, *et al* Challenges facing menstruating adolescents: A reproductive health approach. *Reproductive Health Journal*. 2021;1(1):n.p.
 29. Chisholm JM, Zamani R, Negm AM, Said N, Abdel Daiem MM, Dibaj M, Akrami M. Sustainable waste management of medical waste in African developing countries: A narrative review. *Waste Management & Research*. 2021;39(9):1149–63.
 30. Cosner CC. *Industrial hygiene in the pharmaceutical and consumer healthcare industries*. Boca Raton: CRC Press; 2023.
 31. Dong Z, Liu Y, Duan L, Bekele D, Naidu R. Uncertainties in human health risk assessment of environmental contaminants: A review and perspective. *Environment International*. 2015;85:120–32.
 32. Efobi CC, Nri-ezedi CA, Madu CS, Obi E, Ikediashi CC, Ejiofor O. A retrospective study on gender-related differences in clinical events of sickle cell disease: A single-centre experience. *Tropical Journal of Medical Research*. 2023;22(1):137–44.
 33. Elumalai V, Brindha K, Lakshmanan E. Human exposure risk assessment due to heavy metals in groundwater by pollution index and multivariate statistical methods: A case study from South Africa. *Water*. 2017;9(4):234.
 34. Fargnoli M, Lombardi M. Preliminary human safety assessment (PHSA) for the improvement of the behavioral aspects of safety climate in the construction industry. *Buildings*. 2019;9(3):69.
 35. Fontes C, Hohma E, Corrigan CC, Lütge C. AI-powered public surveillance systems: Why we (might) need them and how we want them. *Technology in Society*. 2022;71:102137.
 36. Friis RH. *Occupational health and safety for the 21st century*. Burlington: Jones & Bartlett Publishers; 2015.
 37. Ganiyu IO. A conceptual framework to measure the effectiveness of work-life balance strategies in selected manufacturing firms, Lagos metropolis, Nigeria [dissertation]. Lagos: n.p.; 2018.
 38. Guo P, Tian W, Li H. Dynamic health risk assessment model for construction dust hazards in the reuse of industrial buildings. *Building and Environment*. 2022;210:108736.
 39. Gutterman AS. Environmental, health and safety committee. *Health and Safety Committee*. 2020;December 1:n.p.
 40. Guzman J, Recoco GA, Padrones JM, Ignacio JJ. Evaluating workplace safety in the oil and gas industry during the COVID-19 pandemic using occupational health and safety vulnerability measure and partial least square structural equation modelling. *Cleaner Engineering and Technology*. 2022;6:100378.
 41. Gwenzi W, Chaukura N. Organic contaminants in African aquatic systems: Current knowledge, health risks, and future research directions. *Science of the Total Environment*. 2018;619:1493–514.
 42. Hassam SF, Hassan ND, Akbar J, Esa MM. AI-enabled real-time workplace health monitoring system. *Greetings from Rector of Bandung Islamic University Prof. Dr. H. Edi Setiadi, SH, MH*. 2023;98:n.p.
 43. Haupt TC, Pillay K. Investigating the true costs of construction accidents. *Journal of Engineering, Design and Technology*. 2016;14(2):373–419.
 44. Herath HMKMB, Mittal M. Adoption of artificial intelligence in smart cities: A comprehensive review. *International Journal of Information Management Data Insights*. 2022;2(1):100076.
 45. Hughes BP, Anund A, Falkner T. A comprehensive conceptual framework for road safety strategies. *Accident Analysis & Prevention*. 2016;90:13–28.
 46. Ikepogu MA. Implementation of occupational safety and health management system in reducing ergonomic risk among certified and uncertified automotive industry workers. *Occupational Health Journal*. 2015;1(1):n.p.
 47. Ikwanusi UF, Azubuike C, Odionu CS, Sule AK. Leveraging AI to address resource allocation challenges in academic and research libraries. *IRE Journals*. 2022;5(10):311.
 48. Ilankoon IMSK, Ghorbani Y, Chong MN, Herath G, Moyo T, Petersen J. E-waste in the international context—A review of trade flows, regulations, hazards, waste

- management strategies and technologies for value recovery. *Waste Management*. 2018;82:258–75.
49. Ingrao C, Faccilongo N, Di Gioia L, Messineo A. Food waste recovery into energy in a circular economy perspective: A comprehensive review of aspects related to plant operation and environmental assessment. *Journal of Cleaner Production*. 2018;184:869–92.
 50. Jetha A, Bakhtari H, Rosella LC, Gignac MA, Biswas A, Shahidi FV, *et al* Artificial intelligence and the work–health interface: A research agenda for a technologically transforming world of work. *American Journal of Industrial Medicine*. 2023;66(10):815–30.
 51. Ji Z. Optimising manufacturing industrial production layout for occupational health and safety. *Manufacturing Health Journal*. 2019;1(1):n.p.
 52. Jilcha K, Kitaw D. A literature review on global occupational safety and health practice & accidents severity. *International Journal for Quality Research*. 2016;10(2):n.p.
 53. John PA. Artificial intelligence technology application and occupational safety in downstream petroleum industries in Greater Accra [dissertation]. Cape Coast: University of Cape Coast; 2023.
 54. Joseph AJ. Health, safety, and environmental data analysis: A business approach. Boca Raton: CRC Press; 2020.
 55. Jung S, Woo J, Kang C. Analysis of severe industrial accidents caused by hazardous chemicals in South Korea from January 2008 to June 2018. *Safety Science*. 2020;124:104580.
 56. Kamunda C, Mathuthu M, Madhuku M. Health risk assessment of heavy metals in soils from Witwatersrand Gold Mining Basin, South Africa. *International Journal of Environmental Research and Public Health*. 2016;13(7):663.
 57. Kasperson RE, Kasperson JX, Hohenemser C, Kates RW, Svenson O. Managing hazards at PETROCHEM Corporation. In: *Corporate management of health and safety hazards*. Routledge; 2019. p. 15–41.
 58. Keating GC. Is cost-benefit analysis the only game in town? *S. Cal. L. Rev*. 2017;91:195.
 59. Khalid S, Shahid M, Natasha B, Bibi I, Sarwar T, Shah AH, *et al* A review of environmental contamination and health risk assessment of wastewater use for crop irrigation with a focus on low- and high-income countries. *International Journal of Environmental Research and Public Health*. 2018;15(5):895.
 60. Kirwan B. A guide to practical human reliability assessment. Boca Raton: CRC Press; 2017.
 61. Lee J, Cameron I, Hassall M. Improving process safety: What roles for digitalization and Industry 4.0? *Process Safety and Environmental Protection*. 2019;132:325–39.
 62. Lewis KA, Tzilivakis J, Warner DJ, Green A. An international database for pesticide risk assessments and management. *Human and Ecological Risk Assessment: An International Journal*. 2016;22(4):1050–64.
 63. Loeppke RR, Hohn T, Baase C, Bunn WB, Burton WN, Eisenberg BS, *et al* Integrating health and safety in the workplace: How closely aligning health and safety strategies can yield measurable benefits. *Journal of Occupational and Environmental Medicine*. 2015;57(5):585–97.
 64. Lohse R, Zhivov A. Deep energy retrofit guide for public buildings: Business and financial models. Cham: Springer; 2019.
 65. McIntyre A, Scofield H, Trammell S. Environmental health and safety (EHS) auditing. In: *Handbook of Occupational Safety and Health*. 2019;613–37.
 66. Muley A, Muzumdar P, Kurian G, Basyal GP. Risk of AI in healthcare: A comprehensive literature review and study framework. *arXiv preprint arXiv:2309.14530*. 2023.
 67. Nagaty KA. IoT commercial and industrial applications and AI-powered IoT. In: *Frontiers of Quality Electronic Design (QED) AI, IoT and Hardware Security*. Cham: Springer International Publishing; 2023. p. 465–500.
 68. Narayanan DK, Ravoof AA, Jayapriya J, Revathi G, Murugan M. Hazards in oil, gas, and petrochemical industries. In: *Crises in Oil, Gas and Petrochemical Industries*. Elsevier; 2023. p. 71–99.
 69. Ndegwa PW. Perceptual measures of determinants of implementation of occupational safety and health programmes in the manufacturing sector in Kenya [dissertation]. 2015.
 70. Nunfam VF, Adusei-Asante K, Van Etten EJ, Oosthuizen J, Adams S, Frimpong K. The nexus between social impacts and adaptation strategies of workers to occupational heat stress: A conceptual framework. *International Journal of Biometeorology*. 2019;63:1693–706.
 71. Nwaogu JM. An integrated approach to improve mental health among construction personnel in Nigeria. *Occupational Health Journal*. 2022;1(1):n.p.
 72. Nwaogu JM, Chan AP. Evaluation of multi-level intervention strategies for a psychologically healthy construction workplace in Nigeria. *Journal of Engineering, Design and Technology*. 2021;19(2):509–36.
 73. Obi ES, Devdat LNU, Ehimwenma NO, Tobalesi O, Iklaki W, Arslan F. Immune thrombocytopenia: A rare adverse event of vancomycin therapy. *Cureus*. 2023;15(5):n.p.
 74. Odionu CS, Azubuike C, Ikwanusi UF, Sule AK. Data analytics in banking to optimize resource allocation and reduce operational costs. *IRE Journals*. 2022;5(12):302.
 75. Oh J. Innovation in HSE management for sustainable development [master's thesis]. 2023.
 76. Olabode SO, Adesanya AR, Bakare AA. Ergonomics awareness and employee performance: An exploratory study. *Economic and Environmental Studies*. 2017;17(44):813–29.
 77. Olawepo Q, Seedat-Khan M, Ehiane S. An overview of occupational safety and health systems in Nigeria. *Alternation*. 2021.
 78. Olu O. Resilient health system as conceptual framework for strengthening public health disaster risk management: An African viewpoint. *Frontiers in Public Health*. 2017;5:263.
 79. Oranusi SU, Dahunsi SO, Idowu SA. Assessment of occupational diseases among artisans and factory workers in Ifo, Nigeria. *Occupational Health Journal*. 2014;1(1):n.p.
 80. Osakwe KA. The possibilities of simultaneous operation (SIMOPs) and practicality of positive pressure habitat in a hazardous industry: Where process safety meets occupational hygiene. *Current Journal of Applied Science and Technology*. 2021;40(13):28–37.
 81. Patel V, Chesmore A, Legner CM, Pandey S. Trends in workplace wearable technologies and connected-worker solutions for next-generation occupational safety, health, and productivity. *Advanced Intelligent Systems*. 2022;4(1):2100099.
 82. Podgorski D, Majchrzycka K, Dąbrowska A, Gralewicz G, Okrasa M. Towards a conceptual framework of OSH

- risk management in smart working environments based on smart PPE, ambient intelligence and the Internet of Things technologies. *International Journal of Occupational Safety and Ergonomics*. 2017;23(1):1–20.
83. Popenorf W. Industrial hygiene control of airborne chemical hazards. CRC Press; 2019.
 84. Purohit DP, Siddiqui NA, Nandan A, Yadav BP. Hazard identification and risk assessment in construction industry. *International Journal of Applied Engineering Research*. 2018;13(10):7639–67.
 85. Redinger C. Benchmarking in international safety and health. In: *Global Occupational Safety and Health Management Handbook*. CRC Press; 2019. p. 95–112.
 86. Ruhrer B. The value of occupational health nursing. 2016.
 87. Sabeti S. Advancing safety in roadway work zones with worker-centred augmented reality: Assessing the feasibility, usability, and effectiveness of AR-enabled warning systems [dissertation]. The University of North Carolina at Charlotte; 2023.
 88. Schulte PA, Iavicoli I, Fontana L, Leka S, Dollard MF, Salmen-Navarro A, *et al* Occupational safety and health staging framework for decent work. *International Journal of Environmental Research and Public Health*. 2022;19(17):10842.
 89. Shad MK, Lai FW, Fatt CL, Klemenš JJ, Bokhari A. Integrating sustainability reporting into enterprise risk management and its relationship with business performance: A conceptual framework. *Journal of Cleaner Production*. 2019;208:415–25.
 90. Shi B, Su S, Wen C, Wang T, Xu H, Liu M. The prediction of occupational health risks of benzene in the printing industry through multiple occupational health risk assessment models. *Frontiers in Public Health*. 2022;10:1038608.
 91. Shi H, Zeng M, Peng H, Huang C, Sun H, Hou Q, *et al* Health risk assessment of heavy metals in groundwater of Hainan Island using the Monte Carlo simulation coupled with the APCS/MLR model. *International Journal of Environmental Research and Public Health*. 2022;19(13):7827.
 92. Sileyew KJ. Systematic industrial OSH advancement factors identification for manufacturing industries: A case of Ethiopia. *Safety Science*. 2020;132:104989.
 93. Tamoor M, Imran HM, Chaudhry IG. Revolutionizing construction site safety through artificial intelligence. *Journal of Development and Social Sciences*. 2023;4(3):1099–104.
 94. Tranter M. Occupational hygiene and risk management. Routledge; 2020.
 95. Uwumiro F, Nebuwa C, Nwevo CO, Okpugie V, Osemwota O, Obi ES, *et al* Cardiovascular event predictors in hospitalized chronic kidney disease (CKD) patients: A nationwide inpatient sample analysis. *Cureus*. 2023;15(10):n.p.
 96. Wollin KM, Damm G, Foth H, Freyberger A, Gebel T, Mangerich A, *et al* Critical evaluation of human health risks due to hydraulic fracturing in natural gas and petroleum production. *Archives of Toxicology*. 2020;94:967–1016.
 97. Wood MH, Fabbri L. Challenges and opportunities for assessing global progress in reducing chemical accident risks. *Progress in Disaster Science*. 2019;4:100044.
 98. Xiao J, Xu X, Wang F, Ma J, Liao M, Shi Y, *et al* Analysis of exposure to pesticide residues from traditional Chinese medicine. *Journal of Hazardous Materials*. 2019;365:857–67.
 99. Xiong K, Kukec A, Rumrich IK, Rejc T, Pasetto R, Iavarone I, *et al* Methods of health risk and impact assessment at industrially contaminated sites: A systematic review. 2018.
 100. Yang S, Sun L, Sun Y, Song K, Qin Q, Zhu Z, *et al* Towards an integrated health risk assessment framework of soil heavy metals pollution: Theoretical basis, conceptual model, and perspectives. *Environmental Pollution*. 2023;316:120596.
 101. Zanke P. Exploring the role of AI and ML in workers' compensation risk management. *Human-Computer Interaction Perspectives*. 2022;2(1):24–44.
 102. Zurub HH. The effectiveness of the occupational health and safety management system in the United Arab Emirates [dissertation]. Aston University; 2021.