Artificial Intelligence in Occupational Health and Safety Risk Management of Construction and Mining Sectors – Advances and Prospects

ABSTRACT

Artificial intelligence (AI) has gained much popularity in various sectors and has found applications in multiple areas, including occupational health and safety risk management of the high-risk construction and mining sectors. This review presents the advances in AI applications in these sectors and synthesizes their barriers for better prospects. In the construction sector, AI can be employed in building information modeling during the design stage to identify and deal with the hazards of building models. AI can be deployed in construction sites through computer vision, sensor networks, knowledge-based systems, and machine learning to capture real-time site conditions, analyze the videos or pictures captured, and provide feedback to workers for appropriate responses. A similar setup involving the same components is also used for managing the occupational health and safety risks of surface or underground mining, particularly for monitoring the environmental conditions, detecting the presence of hazardous gases, and identifying hazards in locations that are remote and difficult to assess. Sensors can be attached to personal protective equipment and watches and the signals transmitted via Bluetooth to permit data collection for analysis and response by AI. In the oil and gas sector, sensors are extensively used to collect process safety data from wells, pipelines, valves, etc. for analytical and predictive AI. AI, especially, machine learning is used to create personalized training for workers based on their learning pace and characteristics. However, the major barriers identified are high cost, lack of support and skilled employees, ethical issues, and the uncertainty of AI. .

Keywords: artificial intelligence, Internet of Things, machine learning; network; sensors; risk management

1. INTRODUCTION

Every year, 2.3 million workers die from work-related accidents or diseases, which is equivalent to over 6000 deaths every day [1]. Approximately 340 million occupational accidents are reported, and 160 million people are directly affected by occupational diseases annually. In fact, occupational diseases are a major cause of death among workers, and exposure to hazardous substances alone contributes to an estimated 651279 deaths annually [1]. Accidents occur more frequently in the construction industry than in other industries. Typically, the construction industry contributes to more than 150000 accidents and injuries on an annual basis. It was over 70% more likely to have injuries than other industries [2]. Occupational health and safety (OHS) management has been increasingly emphasized to safeguard workers from work-related incidents and diseases [3] . Even so, it fails to totally prevent work-related incidents from occurring, and it often requires continual commitment and improvement to protect workers more effectively.

Ensuring the safety, health, and welfare of workers involves substantial investment and commitment but is rewarding in the sense that it could bring long-term cost savings through the reduction of compensation claims, legal fees, and insurance premiums [4]. Additionally, it can improve staff relations and morale as staff perceive that employers care about their well-being and value their contribution. It also gives companies a competitive advantage through building reputation, trust, and brand [4]. The health and safety of a workplace is typically ensured through a systematic approach called OHS management. OHS management involves identifying, assessing, and controlling the hazards and risks that may arise from or affect the workplace. It includes policy establishment, goal-setting, implementation of policies, systems, and standards, as well as record-keeping to monitor and improve OHS performance [5].

OHS risk management plays a central role in OHS management. It is the specific approach employed to identify, assess, and control risks associated with work activities and workplaces, which is an important aspect of occupational health and safety management [6]. It aims to prevent or minimize the occurrence and consequences of work-related injuries, illnesses, and incidents, thus improving the OHS performance of an organization [7]. It commonly involves delineating scope, context, and criteria for risk management, considering an organization's goals, expectations, and issues [8]. It provides the platform for communication and consultation with stakeholders to garner their involvement, feedback, and support. It incorporates risk assessment, which has the pivotal function of identifying occupational hazards and evaluating occupational risks using appropriate methods and tools [8]. Subsequent to risk assessment, the risks are eliminated or reduced to an acceptable level following the hierarchy of control. The risk control measures require monitoring to ensure their effectiveness and compliance. The risk management process is reviewed periodically to identify opportunities for improvement and learning [8]. However, the current practices of OHS risk management may face the challenges of having low compliance with OHS standards and regulations due to weak enforcement and incentives. The rapid changes and emerging challenges in the work environment can pose new and complex OHS risks [9]
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Artificial intelligence (AI) is the ability of a computer system or a robot to perform tasks that normally require human intelligence and these tasks include understanding language, recognizing images, making decisions, or solving problems [10]. AI can be applied to diverse areas, such as healthcare, education, entertainment, and finance. Al offers the benefits of enhancing human capabilities and productivity, for instance by automating tedious or dangerous tasks, improving accuracy and efficiency, or providing new insights and solutions [10]. The application of AI in OHS risk management can facilitate OHS risk management by automating hazardous or repetitive tasks, detecting and alerting potential risks, or providing guidance and training for workers. Al enables robots or drones to perform inspections, maintenance, or repairs in dangerous environments, such as mines, power plants, or construction sites [11]. Furthermore, Al facilitates the collection and analysis of data related to the physical, mental, and emotional states of workers, hence, the monitoring and improvement of their well-being and performance. With these data, Al provides feedback and support to workers by giving early warnings or interventions to prevent burnout, depression, or anxiety [10]. Al is helpful for OHS training as it can create realistic and immersive simulations or scenarios, particularly for emergency response training, which offers vivid learning experiences to workers. This permits workers to visualize various emergencies at workplaces better and handle these situations more effectively [11].

With the rise of Al and increasing use of Al in diverse sectors, this review aims to systematically present the advances in the applications of Al in various aspects of OHS risk management across the construction, mining and oil and gas sectors. It aims to synthesize the barriers stemming from the employment of AI in these sectors to improve its prospects. This review contributes to a better understanding of the functions and performances of Al in OHS risk management to enable the optimization of their applications. Insights into its limitations permit further studies aiming to improve the integration of AI with OHS risk management.

2. APPLICATIONS OF AI IN OHS RISK MANAGEMENT

The roles of AI in OHS management revolve around automating tasks that are hazardous, repetitive, or physically demanding through the use of robots or cobots. It monitors and manages workers using real-time data fed by different sources comprising sensors, cameras, and wearables, thus contributing to OHS surveillance, exposure reduction, and providing early warnings of stress, health problems, and fatigue [12]. It also can analyze large amounts of data to identify patterns, trends, and risks in OHS performance due to the incorporation of machine learning or predictive analytics [11].

2.1 AI in the Construction Sector

The construction sector is one of the most hazardous industries in terms of OHS risks. The common OHS risks associated with the construction sector are 1) traumatic injuries due to falls, electrical shock, machinery, tools, or vehicles, 2) exposure to hazardous chemical substances such as cement, asbestos, dust, and solvents, 3) physical hazards arising from exposure to noise, vibration, heat, cold, or radiation, and 4) ergonomic hazards including poor posture, manual handling, or repetitive motion [13]' [14]. These risks can produce multiple health problems inflicting construction workers, such as musculoskeletal disorders, respiratory diseases, noise-induced hearing loss, and dermatitis [13].

AI has provided an avenue to reduce these risks. In the OHS risk management of the construction sector, AI, in the forms of machine learning, computer vision, knowledge-based systems, and natural language processing, has been introduced or developed [15]. Computer vision involves capturing images using specialized cameras and employing sophisticated algorithms to process and analyze the images produced for decision-making. The knowledge-based system centers on feeding existing knowledge to an inference engine with a user interface that enables users to interact with the engine. The knowledge base is essentially a collection of expert knowledge, experiences, or past cases useful for decision-making [16]. A Knowledge-based system can be divided into 1) expert systems with the knowledge base comprising specific expert knowledge or experience in a particular sector to simulate experts' decision-making for problem-solving, 2) case-based reasoning system where the knowledge base comprising essentially experiences or past cases is input to the system for critical analysis, interpretation, or prediction. It also relies on expert knowledge for the selection of appropriate experiences or cases, 3) intelligence tutoring systems, which simulate human tutors and can provide customized instruction or feedback to learners. They are helpful for OHS training, and 4) database management system, which is a software system with the functions of storing, organizing, and manipulating data in a structured and consistent way. It serves as the knowledge base and supports expert systems by providing data storage, processing, and management [17]. Natural language processing is a branch of AI that creates systems capable of understanding and manipulating human language, such as text or speech. It is frequently used for speech-to-text conversion, natural language generation and understanding, and text summarization [15].
Zhang et al. developed a framework to identify fall hazards in the planning stage of construction projects with algorithms capable of checking safety rules automatically [18]. The framework serves to incorporate safety into building information modeling and has been tested on the model of a construction project. The tool was observed to have a good ability to detect unprotected slab edges and recommend the installation of a guardrail system according to safety rules. The tool is also able to suggest installation and removal work in

addition to giving options and procedures to ensure adequate fall protection in line with the guidelines during the design and planning stages [18]. Nonetheless, the framework requires checking to ensure the validity of the fall protection measures suggested in fast-changing construction projects. The level of detail of the tool also needs further improvement [18]. The framework is a typical example of an expert system with safety rules as inputs to the knowledge base.

Another study focused on developing an automated system for safety monitoring of construction activities. The system is cloud-based and enables real-time monitoring of construction sites [19]. It utilizes Bluetooth low-energy technology for location detection, building an information model for hazard identification, and a cloud-based platform for communication of safety issues (Figure 1) The system was found to successfully detect unsafe conditions on-site and analyze how the risks could impact the workers based on their real-time positioning [19]. The system is akin to computer vision, but it uses Bluetooth for worker positioning instead of cameras to generate images. This enables the algorithm to analyze the risks the workers are exposed to. In a separate study that employed computer vision or its variant, a radio-frequency identification localization system was integrated with building information modeling and cloud computing for construction site management. The system with localization and visualization functions has the potential to improve the safety management of construction sites [20]. Machine learning algorithms comprising boosted trees and deep learning have been used to analyze causes of injuries in the power infrastructure and predict injuries [21]. The system was reported to have a better predictive performance by comparing the predicted values against the observed values, with deep feedforward neural networks yielding the best performance. This predictive case-based reasoning system is beneficial for safety risk management in the power infrastructural sector [21].

Recognizing the limitations of assessing the risks of occupational incidents qualitatively, Kang et al. developed a framework that integrates interpretable machine learning and conventional analysis [22]. The framework has been trained with a large sample of injured workers to identify the key factors that influence the severity of occupational incidents, which is presented as lost workdays. The number of lost workdays determines if an injury is classified as moderate or major [22]. The framework revealed that the most experienced and least experienced workers require interventions via increasing attentiveness and reinforcing safety training, respectively, and it is crucial to manage defective personal protective equipment [22]. A novel graph-based framework was also introduced to effectively process written safety rules and images to facilitate the identification of occupational hazards [23]. The framework uses natural language processing to automatically extract regulatory texts and present the most important information (Figure 1) [23]. It also integrates deep learning for object detection and geometric relationship analysis for individual detection, to process on-site images. By incorporating computer vision and natural language processing, this framework facilitates hazard identification and could successfully spot hazards related to working on height and operating a grinder [23].

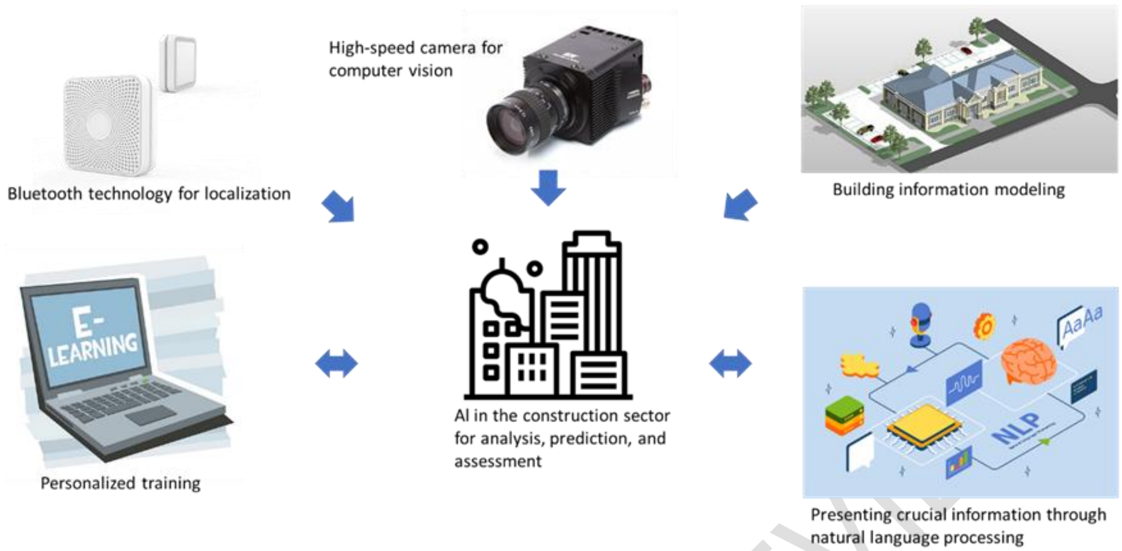

Fig. 1. Applications of AI in the construction sector

Text classification has been conducted for grouping safety standards according to the causes and types of offenses [24]. This enables safety practitioners to relate safety offenses to the relevant safety standards. To effectively do so, the groups or labels for text classification were determined and weighting schemes were applied to determine the weights of the groups. In essence, the text classification method comprises text preprocessing, feature section, feature weighting, and performance evaluation [24]. The relative performance of the text classification and the satisfaction levels of the text classification labels can be predicted with two candidate labels, namely fall protection issues and violation causes. The method provides the basis for text classification using standard machine learning to improve the application of natural language processing in construction safety inspection [24]. Additionally, the popularization of building information modeling has enabled safety management to be incorporated into the early design and planning stages of construction projects (Figure 1). An automated checking function has been developed to enable simulation and visualization of the movements of workers on scaffolds over building information models [25]. The framework has computational algorithms that identify safety hazards arising from the activities of workers on scaffolds to facilitate the formulation of preventive measures. It could be added to building information modeling software as a plug-in and offers the advantage of singling out safety hazards that are overlooked by project managers [25]. Overall, computer vision has gained much popularity in construction safety management. In addition to the studies mentioned above, Zhang proposed a machine vision technology to manage the safety of civil engineering projects, which integrates real-time target detection, spatial analysis between construction scenes and targets, and an early warning platform (Figure 1) [26]. This enables early warnings to be triggered upon the detection of a predefined unsafe condition.

AI is becoming more prevalent in construction safety training. A Bayesian-based knowledge tracking model has been built to suggest training materials based on the learning pace of an employee (Figure 1) [27]. The model can predict an employee's performance using data such as cognitive abilities and past training records. It can calculate the probability of an employee mastering construction safety concepts and generate personalized suggestions for future training to increase training effectiveness [27]. In another study, an AI-facilitated real-time personalized safety training model was put together. The model uses a user-oriented simulation system integrating GPS and cloud computing [28]. The system collects information related to hazards, corresponding safety instructions, and project information, which is then processed and delivered to workers based on their job characteristics to improve their safety awareness [28].

2.2 AI in the Mining Sector

The mining sector is also a high-risk sector where accidents involving heavy machinery, explosives, and hazardous substances are likely to occur. These accidents can result in injuries, fatalities, or disabilities. Mining exposes workers to dust, gases, and fumes, which can cause lung diseases such as silicosis, coal workers' pneumoconiosis, asbestosis, and cancer. Mining generates high levels of noise, which can damage the hearing of workers and lead to industrial deafness [29]. Therefore, it is crucial to manage the risks in the sector and the emergence of AI could potentially increase the efficiency of risk management. Yedla et al. employed machine learning models comprising artificial neural networks, decision trees, and random forests to analyze the outcomes of mining accidents [30]. These models demonstrated better performance than the conventional logistic regression model in predicting accident outcomes. The key predictors of days away from work are mining experience, shift start time, and accident time [30]. As with the construction sector, computer vision utilizing sensors has been widely employed in the mining sector. A blue-tooth-based underground navigation system capable of monitoring underground mining activities has been developed. This was enabled by an underground Bluetooth network [31] .

Exposure to toxic gases is a major hazard in the mining industry, and detecting these gases without any technological aids could be challenging. An attempt has been made to develop a fully automated remote monitoring framework that relies on wireless sensors (Figure 2). It incorporates Ohm's law, mobile sensing, and a decision-making AI [32]. The framework has been tested on real-life applications and was designed to mimic the knowledge of safeguard engineers concerning toxic gas exposure. It aims to provide early warnings when risks are detected [32]. This framework combines computer vision and an expert system for risk management of underground mining. Sensor technology has gained much popularity in the OHS risk management of the mining sector. In another study, sensors attached to personal protective equipment, such as hard hats and safety glasses, were connected to smartphones and smartwatches to collect data on underground mining hazards (Figure 2) [33]. This has enabled real-time information and warnings to be provided to raise situation awareness. The technology can also predict OHS incidents to enable timely intervention [33]. A novel fuzzy logic system has been tested to assess fire risk and severity in an underground coal mine. It is worth noting that this system also relies on extensive sensor nodes to collect environmental data, such as gas concentrations, temperature, and humidity [34]. These data are sent to an observation system with a fuzzy model incorporated for real-time decision-making. The fuzzy model is comparable to an offline monitoring system that requires manpower and expert inputs [34].

Fig. 2. Applications of AI in the mining sector

Furthermore, the Internet of Things and an autonomous robot have been employed to monitor the safety of underground mines [35]. The autonomous robot was integrated with a wireless sensor network, which enabled it to access areas in an underground mine not reachable by humans (Figure 2). The sensor network could collect data on the presence and concentrations of hazardous gases, availability of oxygen, air temperature, air velocity, and humidity of the mines [35]. Besides, they can capture data on mine water quality, such as pH, sulfate content, electrical conductivity, and heavy metal contents. The robot can maintain instruments for the Internet of Things, which controls the robot and sensors. Using a robot significantly reduces the risks of accessing unknown areas in an underground mine for maintenance or mining activities [35]. Additionally, the Internet of Things has found potential applications in lockout/tagout procedures by establishing an intelligent machine monitoring system based on the Internet of Things [36]. Defective lockout/tagout procedures have been identified as a major contributor to machine-related incidents. The monitoring system comprises a proof-of-concept system and a subsequent system upgrade with more sensors, safety metrics, and algorithms incorporated. The former aims to provide real-time information on intrusions, lockout/tagout, and safety status of a concrete batch plant without involving automation [36]. In the second step, the design is optimized according to the ultimate use of the system for large-scale surface mines. The system can be expanded to include predictive failure analysis based on the database established in the early stage and proximity detection with more sensors installed [36].

A smart safety helmet incorporating a gas sensor has been developed to detect methane and carbon monoxide and transmit the data to a control center through a wireless module on the helmet. The data triggers an alarm when methane or carbon monoxide concentrations exceed the limits [37]. A smart safety helmet has also been developed to monitor workers' exposure to respirable silica dust at surface mines [38]. The helmet has a light video camera mounted. Dust exposure is measured with a dust monitor carried by mine workers, which can gather video and dust exposure data every two seconds [38]. The information stored in the monitor can be downloaded and analyzed by software and subsequently used for implementing exposure control [38]. An intelligent eyewear technology has been introduced for the mining sector, particularly hard rock mining. The intelligent eyewear offers a time-managing function for mining equipment operation, useful mining information, and production process monitoring [39]. The eyewear is equipped with a global positioning system (GPS) and communication features to exchange information. The glasses act as smart displays to convey mining operation information conveniently. The camera attached to the glasses can capture images or videos of the operations and send them to a control center [39]. Like smart eyewear, smartwatches help communicate with mine workers about mining operations, alert them on the mining risks, and permit them to send crucial information on mining. Smartwatches have software that facilitates the navigation of information related to mining operations and logistics [39].

As with the construction sector, applications of AI in the mining sector mainly focus on computer vision through cameras and sensors installed on devices such as robots, eyewear, safety helmets, and watches. These devices either have an in-built knowledge-based system or are connected with one via wireless technology for the exchange of information essential for OHS risk control in mining operations. The exchange of information between devices and the data management system, often a cloud, requires the Internet of Things. The devices can be used alone or combined, as with a safety helmet and a smartwatch to capture and display information.

2.3 AI in the Oil and Gas Sector

The oil and gas sector is a subset of the mining sector. In Malaysia, 1021 occupational accidents were recorded in the oil and gas sector in 2023 and 18 of the accidents were fatal. The accident frequency rate was 0.69, while the severity rate was 17.97 per million man-hours worked [40]. Globally, the oil and gas sector has an average fatal accident rate of 3.0 per 100,000 workers, higher than the average rate of 2.3 for all industries. The most common types of fatal accidents in the oil and gas sector worldwide are transportation incidents (41%), contact with objects and equipment (25%), and fires and explosions (15%) [41]. Transportation accidents in the oil and gas sector are caused by vehicle collisions when transporting workers and equipment to and from well sites, often in remote areas. The hazards arising from struck-by/caught-in/caught-between constitute three of every five on-site fatalities in the oil and gas sector [41]. These hazards could result from moving vehicles or equipment, falling equipment, and high-pressure lines. Explosions and fires are also significant risks in the oil and gas sector, and they are often caused by flammable gases from wells and production equipment [42]. Workers may be subjected to fall hazards when accessing platforms and equipment high above the ground [43]. They may also need to enter confined spaces such as tanks, vessels, and pits containing hazardous gases or liquids or lacking oxygen [42].

AI can help significantly deal with these hazards. Ibrahim proposed using a wireless sensing technology called ZigBee to collect crucial data from offshore or onshore sites of oil and gas exploration, which are remote or unsafe for human access [44]. ZigBee can have a wide coverage of 40 km through multi-hop communication capability. It allows real-time monitoring of subsea production via wireless connection with remote structures such as valves and metering stations, thus, ensuring timely collection of operational data for timely responses without needing human access to the remote sites [44]. In addition, wireless gas leakage detection systems have been introduced to address the safety concerns associated with leakage of and exposure to toxic and flammable gases plaguing the oil and gas industry [45]. The systems also rely on ZigBee technology, which consists of a network of gas sensors and wireless sensor nodes to form a monitoring system. The systems provided fast response time, measured as the duration between the sending of the first alert and the receiving of the first GPS reading [45]. A linear sensor network consisting of linearly positioned nodes provides an avenue for managing safety risks in oil and gas operations [46]. The network has a custom sensor board and algorithms that keep the network active all the time, detect and locate leakage, and deliver essential messages. It requires low energy to operate, has high data reliability, and reduces latencies [46].

Rashid et al. developed a smart wireless sensor network to detect leaks in pipelines and their severity [47]. The network incorporates wireless communication and machine learning, the latter of which can study and determine the magnitude of leakages via negative pressure waves in the pipelines detected by sensor nodes [47]. As process safety is a crucial aspect of the oil and gas sector, multiple studies focus on ensuring pipeline safety. In another study, a monitoring system combining a GPRS network, Internet, and wireless sensor networks was proposed to monitor the cathodic protection equipment of terrestrial pipelines [48]. The system collects cathode potential data timely and transmits the data to a control center for regulation. The system has been successfully tested and optimized in terms of reliability in data transmission, and energy consumption [48]. Wireless sensor networks were also employed by Jung and Song to establish a safety monitoring system for industrial pipe racks [49]. The system comprises field nodes, field network gateways, and a control server. It was tested on petrochemical plants and was observed to assess the stability of the pipe rack structures and suggest risk management strategies satisfactorily [49]. Similarly, a wireless sensor-based technology with a wide coverage has been established to detect propane leaks. The system was able to detect 91% of propane leaks in 3 days, with a delay of 108 s on average [50]. Sensor-based technology has gained popularity in the oil and gas sector because it enables hazard detection and risk monitoring over large areas and at remote locations in real time with only small delays, thus, providing timely information and permitting timely responses. It is connected to a knowledge-based system, which provides an evaluation of the data gathered and proposes responding strategies based on expert recommendations or guidelines stored [51]. The knowledge-based system, particularly the expert system has also been proposed for OHS and process safety assessment of offshore oil and gas platforms [17]. The assessment system can generate an overall index based on the scores of various OHS aspects of an offshore oil and gas platform. The index scores can be linked to different risk levels, such as high, medium, and low risks using the fuzzy expert system [17]. The fuzzy expert system produces safety scores that are comparable to those of a safety professional [52].

As with the construction sector and the mining sector, the Internet of Things has an important role in the risk management of the oil and gas sector as it serves as a platform to connect items employed for risk management in the sector. An attempt was made to improve the architecture of the Internet of Things to better support the oil and gas value chain. The new architecture can more effectively identify problems in the value to increase business productivity and enhance OHS risk identification [53]. The emergence of digital twins makes virtual replications of physical assets, systems, or processes possible. This helps simulate, monitor, and optimize performance. A digital twin can be updated with real-time data from sensors and is integrable with machine learning and reasoning for decision-making. In the oil and gas sector, a digital twin can help identify and mitigate potential hazards, such as equipment failures, leaks, fires, or explosions, by using real-time data and predictive analytics [54]. It can help improve the training and preparedness of workers by creating realistic scenarios and immersive experiences. It can also enhance collaboration and communication among different stakeholders, such as operators, regulators, and emergency responders, by providing a common platform and a shared view of the situation [54].

Edge computing has come into the limelight in the oil and gas industry. It is a distributed computing framework that allows data to be processed and analyzed closer to their sources

[55]. This can improve response times, save bandwidth, and enable new applications that require low latency and real-time insights. It has better responsiveness and throughput of applications. It is essentially a speedier alternative to a conventional cloud-based system, which powers the Internet of Things more efficiently [55]. With edge computing, the oil and gas sector can better monitor and optimize the performance of its assets, such as pipelines, wells, rigs, and refineries by using real-time data and predictive analytics [56]. This can help identify and mitigate potential hazards, such as equipment failures, leaks, fires, or explosions, and reduce operational costs and environmental impacts [56]. Furthermore, machine learning using the least squares support vector machine has been employed to characterize pipeline operation and leakage in the oil and gas sector. The system can detect and locate pipeline leakage more accurately and precisely [56].

The application of machine learning has permeated the oil and gas industry. Kellogg et al. tested a new machine-learning approach with algorithms trained with a large pool of well data to evaluate the economic feasibility of well maintenance jobs for removing wellbore damage and restoring the natural permeability of a reservoir [57]. Ozigis et al. (2019) proposed using machine learning to identify oil-impacted land [58]. The system utilizes spectral bands provided by Landsat 8 and vegetation health indices to differentiate land plots contaminated with oil spills from those free of oil. The system can help control the risk arising from oil and gas accidents significantly, provided that the oil-polluted and oil-free plots are properly classified [58]. The approaches of AI employment in the oil and gas sector are largely similar to the construction and the overarching mining sector involving extensive sensor networks to collect copious data that are fed to a knowledge-based or machine learning system for analysis, decision-making, prediction, and suggestions of responses. All these rely on a powerful data management system to store and quickly retrieve data for timely response. The Internet of Things is a versatile platform that connects different devices, particularly robotics, sensors, and control centers. It enables digital twins mimicking a facility or process to be created. Unlike the construction and mining sectors, the use of computer vision is less prevalent in the oil and gas sector, especially in harsh environments such as offshore platforms and subsea pipelines where the cameras may not function optimally.

3. CONCLUSION

The rise of AI has facilitated OHS risk management, which conventionally relies on expert judgment and may be constrained by the accessibility of sites. The common AI approaches are computer vision, sensor networks, knowledge-based systems for decision-making, machine learning for data analysis, prediction, and evaluation, the Internet of Things to enable communication of different devices or components connected to a network, and a data management system for storage, processing, and retrieval of data. AI has been extensively developed for use in the construction and mining sectors. In the construction sector, AI can be employed as early as the design and planning stage by merging with building information modeling to identify hazards and manage risks of building or project models. Computer vision can capture the actual conditions of construction and mining sites and subsequently feed the data to a knowledge-based or machine-learning system for hazard identification and risk assessment, and in some instances, prediction of the probability of a safety incident. Similarly, extensive sensor networks established on-site facilitate the collection of crucial data related to site conditions for analysis by a knowledge-based or machine-learning system. These systems can provide warning and response strategies. AI is also helpful in creating personalized training for construction and mining workers. The advancements in the Internet of Things and database management systems enable the speed of data transmission to be substantially improved and digital twins to be created for more efficient monitoring.

Despite that AI has been successfully tested experimentally, its industrial applications may not be straightforward. The barriers of AI need to be addressed to improve their practical applications in OHS risk management. These barriers are:

1. The high cost of AI implementation and maintenance may limit its accessibility and affordability for small and medium-sized enterprises.
2. The lack of top-down support and skilled employees trained in AI may hinder the integration and adoption of AI solutions in OHS practices.
3. The ethical, legal, and social implications of AI, such as algorithmic bias, data privacy, worker surveillance, and accountability, may pose challenges for OHS equity and governance.
4. The uncertainty and complexity of AI may create new and emerging risks for OHS, such as human-machine interaction, psychosocial stress, and cyberattacks.

These barriers require multidisciplinary research, collaboration, and regulation to ensure can be practically, responsibly, and widely used.

REFERENCES

1. ILO (2024) The enormous burden of poor working conditions. https://www.ilo.org/moscow/areas-of-work/occupational-safety-and-health/WCMS_249278/lang--en/index.htm. Accessed 5 Jan 2024
2. Tyrrell P (2021) 9 Construction Accident & Safety Statistics in 2021. 5 January 2024
3. Uhrenholdt Madsen C, Kirkegaard ML, Dyreborg J, Hasle P (2020) Making occupational health and safety management systems 'work': A realist review of the OHSAS 18001 standard. Saf Sci 129:104843 . https://doi.org/https://doi.org/10.1016/j.ssci.2020.104843
4. IOSH (2021) 10 reasons why health and safety is important to your business. https://www.fieldinsight.com/blog/construction-accident-statistics/. Accessed 5 Jan 2024
5. ILO (2024) Occupational Safety and Health Management Systems. https://www.ilo.org/safework/areasofwork/occupational-safety-and-health-management-systems/lang--en/index.htm. Accessed 5 Jan 2024
6. Tang KHD (2020) A comparative overview of the primary Southeast Asian safety and health laws. Int. J. Work. Heal. Manag. 13:601–632
7. Tang KHD (2021) A Case Study of Asset Integrity and Process Safety Management of Major Oil and Gas Companies in Malaysia. J Eng Res Reports 20:6–19
8. Gul M, Ak MF (2018) A comparative outline for quantifying risk ratings in occupational health and safety risk assessment. J Clean Prod 196:653–664 . https://doi.org/https://doi.org/10.1016/j.jclepro.2018.06.106
9. Tang KHD (2018) Safety performance measurement framework for offshore oil and gas platforms in Malaysia. University of Malaya
10. Moore P V (2019) OSH and the Future of Work: Benefits and Risks of Artificial Intelligence Tools in Workplaces BT - Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management. Human Body and Motion. In: Duffy VG (red). Springer International Publishing, Cham, bll 292–315
11. EU-OSHA (2021) Impact of Artificial Intelligence on Occupational Safety and Health. Bilbao, Spain
12. Adem A, Çakit E, Dağdeviren M (2020) Occupational health and safety risk assessment in the domain of Industry 4.0. SN Appl Sci 2:977 . https://doi.org/10.1007/s42452-020-2817-x

13. Gunduz M, Laitinen H (2018) Construction safety risk assessment with introduced control levels. J Civ Eng Manag 24:11–18
14. Tang KHD (2020) Abating Biomechanical Risks: A Comparative Review of Ergonomic Assessment Tools. J Eng Res Reports 17:41–51 . https://doi.org/https://doi.org/10.9734/jerr/2020/v17i317191
15. Abioye SO, Oyedele LO, Akanbi L, Ajayi A, Davila Delgado JM, Bilal M, Akinade OO, Ahmed A (2021) Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. J Build Eng 44:103299 . https://doi.org/https://doi.org/10.1016/j.jobe.2021.103299
16. Tang KHD, Md. Dawal SZ, Olugu EU (2018) Generating Safety Performance Scores of Offshore Oil and Gas Platforms in Malaysia. Proc One Curtin Int Postgrad Conf 325–331
17. Tang KHD, Md Dawal SZ, Olugu EU (2018) Integrating fuzzy expert system and scoring system for safety performance evaluation of offshore oil and gas platforms in Malaysia. J Loss Prev Process Ind 56:32–45 . https://doi.org/https://doi.org/10.1016/j.jlp.2018.08.005
18. Zhang S, Sulankivi K, Kiviniemi M, Romo I, Eastman CM, Teizer J (2015) BIM-based fall hazard identification and prevention in construction safety planning. Saf Sci 72:31–45 . https://doi.org/https://doi.org/10.1016/j.ssci.2014.08.001
19. JeeWoong P, Kyungki K, K. CY (2017) Framework of Automated Construction-Safety Monitoring Using Cloud-Enabled BIM and BLE Mobile Tracking Sensors. J Constr Eng Manag 143:5016019 . https://doi.org/10.1061/(ASCE)CO.1943-7862.0001223
20. Yihai F, K. CY, Sijie Z, Esau P (2016) Case Study of BIM and Cloud–Enabled Real-Time RFID Indoor Localization for Construction Management Applications. J Constr Eng Manag 142:5016003 . https://doi.org/10.1061/(ASCE)CO.1943-7862.0001125
21. Oyedele A, Ajayi A, Oyedele LO, Delgado JMD, Akanbi L, Akinade O, Owolabi H, Bilal M (2021) Deep learning and Boosted trees for injuries prediction in power infrastructure projects. Appl Soft Comput 110:107587 . https://doi.org/https://doi.org/10.1016/j.asoc.2021.107587
22. Kang K-S, Koo C, Ryu H-G (2022) An interpretable machine learning approach for evaluating the feature importance affecting lost workdays at construction sites. J Build Eng 53:104534 . https://doi.org/https://doi.org/10.1016/j.jobe.2022.104534
23. Chen S, Demachi K, Dong F (2022) Graph-based linguistic and visual information integration for on-site occupational hazards identification. Autom Constr 137:104191 . https://doi.org/https://doi.org/10.1016/j.autcon.2022.104191
24. Chi N-W, Lin K-Y, El-Gohary N, Hsieh S-H (2016) Evaluating the strength of text classification categories for supporting construction field inspection. Autom Constr 64:78–88 . https://doi.org/https://doi.org/10.1016/j.autcon.2016.01.001
25. Kim K, Cho Y, Zhang S (2016) Integrating work sequences and temporary structures into safety planning: Automated scaffolding-related safety hazard identification and prevention in BIM. Autom Constr 70:128–142 . https://doi.org/https://doi.org/10.1016/j.autcon.2016.06.012
26. Zhang Y (2021) Safety Management of Civil Engineering Construction Based on Artificial Intelligence and Machine Vision Technology. Adv Civ Eng 2021:3769634 . https://doi.org/10.1155/2021/3769634
27. Xu S, Sun M, Fang W, Chen K, Luo H, Zou PXW (2023) A Bayesian-based knowledge tracing model for improving safety training outcomes in construction: An adaptive learning framework. Dev Built Environ 13:100111 . https://doi.org/https://doi.org/10.1016/j.dibe.2022.100111
28. Tang N, Hu H, Xu F, Zhu F (2019) Personalized safety instruction system for construction site based on internet technology. Saf Sci 116:161–169 . https://doi.org/https://doi.org/10.1016/j.ssci.2019.03.001

29. Florez-Salas JLT, Ramos-Saira EM, Joo-García CE, Ramos-Alave R, Del Carpio-Delgado F, Laura-De La Cruz KM (2023) Safety and Occupational Health Management System in Mining to Reduce Fatal Accidents in the Mining Industry BT - Perspectives and Trends in Education and Technology. In: Mesquita A, Abreu A, Carvalho JV, Santana C, de Mello CHP (reds). Springer Nature Singapore, Singapore, bll 57–67
30. Yedla A, Kakhki FD, Jannesari A (2020) Predictive Modeling for Occupational Safety Outcomes and Days Away from Work Analysis in Mining Operations. Int. J. Environ. Res. Public Health 17
31. Baek J, Choi Y, Lee C, Suh J, Lee S (2017) BBUNS: Bluetooth Beacon-Based Underground Navigation System to Support Mine Haulage Operations. Minerals 7
32. Osunmakinde IO (2013) Towards Safety from Toxic Gases in Underground Mines Using Wireless Sensor Networks and Ambient Intelligence. Int J Distrib Sens Networks 9:159273 . https://doi.org/10.1155/2013/159273
33. Adjiski V, Despodov Z, Mirakovski D, Serafimovski D (2019) System architecture to bring smart personal protective equipment wearables and sensors to transform safety at work in the underground mining industry. Rud Zb 34:37–44
34. Basu S, Pramanik S, Dey S, Panigrahi G, Jana DK (2019) Fire monitoring in coal mines using wireless underground sensor network and interval type-2 fuzzy logic controller. Int J Coal Sci Technol 6:274–285 . https://doi.org/10.1007/s40789-019-0244-7
35. Günther F, Mischo H, Lösch R, Grehl S, Güth F (2019) Increased safety in deep mining with iot and autonomous robots. In: Mining Goes Digital. CRC Press, bll 603–611
36. McNinch M, Parks D, Jacksha R, Miller A (2019) Leveraging IIoT to Improve Machine Safety in the Mining Industry. Mining, Metall Explor 36:675–681 . https://doi.org/10.1007/s42461-019-0067-5
37. Hazarika P (2016) Implementation of smart safety helmet for coal mine workers. In: 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES). bll 1–3
38. Haas EJ, Cecala AB, Hoebbel CL (2016) Using Dust Assessment Technology to Leverage Mine Site Manager-Worker Communication and Health Behavior: A Longitudinal Case Study. J Progress Res Soc Sci 3:154–167
39. Mardonova M, Choi Y (2018) Review of Wearable Device Technology and Its Applications to the Mining Industry. Energies 11
40. DOSH (2024) Occupational Accident Statistic 2023. https://www.dosh.gov.my/index.php/list-of-documents/statistics/occupational-accident-statistics/occupational-accident-statistic-2023. Accessed 8 Jan 2024
41. UNDRR (2024) Safety Hazards Associated with Oil and Gas. https://www.undrr.org/understanding-disaster-risk/terminology/hips/tl0034. Accessed 8 Jan 2024
42. OSHA (2024) Oil and Gas Extraction. https://www.osha.gov/oil-and-gas-extraction/hazards. Accessed 9 Jan 2024
43. Tang DKH, Leiliabadi F, Olugu EU, Md Dawal SZ binti (2017) Factors affecting safety of processes in the Malaysian oil and gas industry. Saf Sci 92:44–52 . https://doi.org/https://doi.org/10.1016/j.ssci.2016.09.017
44. Ibrahim A (2015) Using ZigBee for Wireless Remote Monitoring and Control. J Energy 2:189–197
45. Aliyu F, Al-shaboti M, Garba Y, Sheltami T, Barnawi A, Morsy MA (2015) Hydrogen Sulfide (H2S) Gas Safety System for Oil Drilling Sites using Wireless Sensor Network. Procedia Comput Sci 63:499–504 . https://doi.org/https://doi.org/10.1016/j.procs.2015.08.375
46. Ali S, Ashraf A, Qaisar SB, Afridi MK, Saeed H, Rashid S, Felemban EA, Sheikh AA (2018) SimpliMote: A Wireless Sensor Network Monitoring Platform for Oil and Gas Pipelines. IEEE Syst J 12:778–789 . https://doi.org/10.1109/JSYST.2016.2597171

47. Rashid S, Akram U, Khan SA (2015) WML: Wireless Sensor Network based Machine Learning for Leakage Detection and Size Estimation. Procedia Comput Sci 63:171–176 . https://doi.org/https://doi.org/10.1016/j.procs.2015.08.329
48. Liu P, Huang Z, Duan S, Wang Z, He J (2015) Optimization for remote monitoring terrestrial petroleum pipeline cathode protection system using graded network. Int J Smart Home 9:51–64
49. Jung J, Song B (2014) The Possibility of Wireless Sensor Networks for Industrial Pipe Rack Safety Monitoring. In: 2014 47th Hawaii International Conference on System Sciences. bll 5129–5134
50. Chraim F, Erol YB, Pister K (2016) Wireless Gas Leak Detection and Localization. IEEE Trans Ind Informatics 12:768–779 . https://doi.org/10.1109/TII.2015.2397879
51. Tang KHD, Md Dawal SZ, Olugu EU (2018) A review of the offshore oil and gas safety indices. Saf Sci 109:344–352 . https://doi.org/https://doi.org/10.1016/j.ssci.2018.06.018
52. Tang DKH, Md Dawal SZ, Olugu EU (2018) Actual safety performance of the Malaysian offshore oil platforms: Correlations between the leading and lagging indicators. J Safety Res 66:9–19 . https://doi.org/https://doi.org/10.1016/j.jsr.2018.05.003
53. Khan WZ, Aalsalem MY, Khan MK, Hossain MS, Atiquzzaman M (2017) A reliable Internet of Things based architecture for oil and gas industry. In: 2017 19th International Conference on Advanced Communication Technology (ICACT). bll 705–710
54. Wanasinghe TR, Wroblewski L, Petersen BK, Gosine RG, James LA, Silva O De, Mann GKI, Warrian PJ (2020) Digital Twin for the Oil and Gas Industry: Overview, Research Trends, Opportunities, and Challenges. IEEE Access 8:104175–104197 . https://doi.org/10.1109/ACCESS.2020.2998723
55. Cao K, Liu Y, Meng G, Sun Q (2020) An Overview on Edge Computing Research. IEEE Access 8:85714–85728 . https://doi.org/10.1109/ACCESS.2020.2991734
56. Knebel FP, Trevisan R, Nascimento GS do, Abel M, Wickboldt JA (2023) A study on cloud and edge computing for the implementation of digital twins in the Oil & Gas industries. Comput Ind Eng 182:109363 . https://doi.org/https://doi.org/10.1016/j.cie.2023.109363
57. Kellogg RP, Chessum W, Kwong R (2018) Machine Learning Application for Wellbore Damage Removal in the Wilmington Field. SPE West. Reg. Meet. D041S011R001
58. Ozigis MS, Kaduk JD, Jarvis CH (2019) Mapping terrestrial oil spill impact using machine learning random forest and Landsat 8 OLI imagery: a case site within the Niger Delta region of Nigeria. Environ Sci Pollut Res 26:3621–3635 . https://doi.org/10.1007/s11356-018-3824-y