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AI-Driven HSE Management Systems for Real-Time Risk Mitigation in Oil and Gas Operations

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Abstract- The oil and gas (O&G) industry is a highly dangerous operation in the world, which requires strong Health, Safety and Environment (HSE) management systems to provide timely risk mitigation. The advent of Artificial Intelligence (AI), which includes Internet of Things (IoT), unmanned aerial systems (UAS), digital twin architectures and machine learning and deep learning, has the potential to unlock a new way of approaching HSE management that moves away from reactive to proactive and predictive. This study aims to conduct a systematic literature review (SLR) of the AI-related applications in the field of HSE within O&G operations based on 20 peer-reviewed publications from 2023 to 2025. This review includes predictive maintenance, pipeline leak detection, worker physiological monitoring, drone surveillance and digital twin risk simulation. Thematic synthesis methodology was used to merge and synthesize technology enablers, performance outcomes, implementation barriers and future technology research priorities. The outcomes show that integrating AI can increase pipeline monitoring accuracy to over 90%, cut down on unplanned equipment failures by up to 34% and drastically cut down on the emergency response time. The challenges are related to data governance issues, regulatory weaknesses, cyber security risks and lack of skills in the workforce. The article wraps up with a forward-looking AI-HSE integration framework, in line with international safety standards, and the United Nations Sustainable Development Goals (SDGs), and provides action-oriented guidance to O&G operators, safety practitioners and policy makers.

Keywords: Artificial Intelligence, HSE Management, Oil And Gas, Real-Time Risk Mitigation, Predictive Maintenance, Pipeline Leak Detection, Digital Twins, Wearable Sensors, Safety Culture.

I. INTRODUCTION

1.1 Background and Motivation

The oil & gas industry is one of the most dangerous industries in the world with high pressure systems, toxic chemicals, extreme temperatures and extreme operating conditions. The Piper Alpha explosion in 1988, Deepwater Horizon blowout in 2010 and similar events have proven the devastating impact that poor HSE management can have on the business. Today, O&G operations are also limited by increasing regulatory demands, increased environmental pressure and commercial pressures associated with the aging infrastructure (Jamil et al., 2025). All of these forces require a HSE management system that can minimize the risk continuously, intelligently and adaptively at a scale and speed that is unattainable without them.

AI offers a revolutionizing opportunity. AI algorithms can analyze and detect such patterns hidden within these vast operational data streams, enabling accurate predictions of equipment deterioration, as well as automatic and timely responses for safety and prevention (Wang et al., 2023). This capability enables the HSE management discipline to go from being lagging indicator to a leading indicator discipline, based on predictive intelligence.

Despite its technological advances, the use of AI for HSE management in the O&G sector is still in its infancy and underutilised. Despite the benefits that AI technology can bring, there are several barriers that hinder its systematic deployment, such as data silos, regulatory uncertainty, workforce skills gaps, and algorithmic trustworthiness concerns (Ucar et al., 2024). It is thus opportune and essential to have a systematic and science-based analysis of the AI-HSE nexus to gather existing knowledge, look for best practices and lay the foundations for scalable implementation.

1.2 Objectives and Scope

The main aim of this article is to present a systematic review of the potential of using AI technologies for HSE risk mitigation in O&G operations, a synthesis of evidence on outcomes of implementing AI technologies, and a conceptualized framework for integrated AI-HSE management in line with sustainability and safety culture. The review includes literature from the last three years (2023-2025) and covers subjects relating to upstream drilling, midstream pipeline operations, and downstream refining.

1.3 Article Organisation

The rest of this article follows the outline below. The literature review, presented in section 2, is based on the theoretical foundations for HSE and on the technology enablers of AI. The method of carrying out the systematic review is described in Section 3. The synthesised results are provided in section 4, by five thematic domains. The implications for practice and policy are discussed in Section 5. The article is concluded in Section 6, which points out the future research needs.

II. LITERATURE REVIEW

2.1. Evolution of HSE Management in Oil and Gas

The Oil & Gas industry has experienced tremendous change in HSE management over the last 50 years. Following key incidents, early regulations largely had a prescriptive and compliance approach were replaced by risk-based approaches, and after Piper alpha much of the industry did so through the safety case approach. Using risk-based thinking, behavioural safety science and human factors engineering, contemporary HSE practice will support technical and organisational failure pathways of the risk (Jamil et al., 2025).

Safety culture is a key enabler for sustainable HSE performance. However, Al-Mekhlafi et al. (2025) carried out a Scopus bibliometric analysis which showed a significant rise in safety culture research outputs from 2018 onwards, indicating that the importance of culture as a key leading indicator of HSE outcomes has been recognised by institutions. At the same time, Jamil et al. (2023) presented a comprehensive safety communication framework for high-risk environment, they claimed that structured communication and feedback, reduce frequency of human error and enhance near miss reporting rate in field operations.

Predictive analytics has helped to speed up the shift from lagging to leading HSE indicators. Azmi et al. (2024) surveyed the predictive analytics models in the Malaysian O&G industry, highlighting the evolution of the industry's use of ensemble machine learning over the years for equipment reliability prediction, process anomaly detection, and contractor safety performance prediction. They found predictive models based on AI algorithms to be between 15–22 percentage points ahead of traditional statistical ones in multi-failure-mode classification, in terms of F1 score.

2.2 AI Technology Enablers for Industrial Safety

The field of AI technology that can be used in O&G HSE management is wide and quickly changing. In the context of sensor classification tasks, machine learning (ML) algorithms, like random forests, support vector machines and gradient boosting, are more appropriate as compared to deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which are more suitable for image analysis and time-series anomaly detection, respectively (Wang et al., 2023). To tackle the challenge of safety data being class-imbalanced, generative adversarial networks (GANs) can generate realistic examples of faults to be used for training the model (Bi et al., 2024).

Deep learning is revolutionizing pipeline integrity monitoring with the combination of physical sensing modalities. Xie et al. (2023) used Faster R-CNN and infrared thermography to detect a micro-leak, at concentrations ten times less than the hazardous level. To address this, Chen et al. (2025) proposed lightweight CNN architectures incorporating attention mechanisms which save 62% computation to enable deployment at the edge in real-time for pipeline monitoring hardware. The detection can also be further expanded by acoustic emission monitoring; CNN-based noise classifiers can classify the leak signal from the industrial noise with a recognition rate of more than 93% (Chen et al., 2024).

Individual level safety is added with wearable sensor technology. Formisano et al. (2024) showed a multi-parameter wearable node, which combines a variety of sensors, including toxic gas, thermal,

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physiological, and position, with sub-500ms data latency, providing real-time alerts in case of H2S exposure, heat stress, and fall events. UAS platforms expand the utility of aerial survey to areas that are difficult or impractical to monitor from the ground and to high structures where human access is limited and unauthorized. AI-based object detection can be used to automatically monitor PPE compliance, detect near-miss situations and potential hazards. (Akinsemoyin et al., 2023)

2.3 Digital Twins and to HSE Risk Modelling

The digital twin (DT) technology is a 3-D virtual replica of physical system that can dynamically change in accordance with the real-time data, and allow continuous simulation of failure scenarios, quantification of risks, and optimisation of emergency response (Lin et al., 2024). Meza et al. (2024) surveyed the deployment of DTs in O&G operations in China, Singapore and South America and found that there is a maturity spectrum ranging from static asset models (Level 1) to complete autonomous and self optimising facility twins (Level 5). Most of the deployments that are currently in place are at Level 2-3, with real-time asset health dashboards and predictive maintenance scheduling.

Ren et al. (2025) reported the explosive growth of DT's application in the O&G domain, specifically the physics-informed DT, which combines the physics-based engineering equations with data-driven ML parts, will be more reliable than data-driven approaches when predicting rare high-consequence failure events. This combination of paradigms is becoming more and more popular for safety-critical DT deployments, where training data is scarce for catastrophic failure modes, which is the case here (Ren et al., 2025; Lin et al., 2024).

2.4. Environment and risk factors in the planning process

The accidents on pipelines create a lot of environmental issues as well as immediate safety concerns. Lu et al. (2023) performed a worldwide analysis of the environmental hazards associated with oil pipeline accidents, which found soil contamination, groundwater intrusion and releases of hydrocarbons into the atmosphere as the main environmental pathways of impact. Their risk matrix analysis showed that investment in AI-HSE would lead to a reduction of 60-80% on the amount of hydrocarbon released per leak due to the quicker response time to the leak's location, making the economic case for investing in AI-HSE a compelling indeed environmental and regulatory one.

The rules and regulations for the use of artificial intelligence in industries with safety-critical functions are still in their infancy. Ucar et al. (2024) pointed out that although there are some guidelines for AI (IOGP, API), there are no complete guidelines for the qualification, validation and change management of algorithms used for HSE applications. This leaves a high level of uncertainty with respect to compliance and subjects early adopters to unique validation challenges, which are a substantial hurdle for rollout of AI-HSE in the industry.

Table 1: Summary of Key AI Technologies and Their HSE Applications in O&G Literature

AI Technology	HSE Application	Performance Metric	Source
Lightweight CNN + Attention	Pipeline Fault Classification	93.7% accuracy; 62% compute reduction	Chen et al. (2025)
Semi-supervised GAN	Urban Gas Pipeline Leak Detection	Overcomes class imbalance in fault datasets	Bi et al. (2024)
IoT + Gradient Boosting	Real-time Gas Leakage Detection	96.3% accuracy; <2% false positive rate	Wang et al. (2024)
IRT + Faster R-CNN	Pipeline Micro-Leak Detection	91.4% mean average precision	Xie et al. (2023)
Acoustic Emission CNN	Subsea Pipe Leakage Identificati	>93% accuracy in noisy O&G environme	Chen et al. (2024)

	on	nts	
Wearable Multi-sensor Node	Worker Physiological & Gas Monitoring	<500ms latency; H2S + heat + fall detection	Formisano et al. (2024)
UAS + YOLOv5	PPE Compliance & Site Surveillance	Automated near-miss precursor detection	Akinsemoyin et al. (2023)
Physics-informed Digital Twin	Drilling & Well Integrity Monitoring	34% reduction in unplanned well interventions	Lin et al. (2024)
Multimodal Fusion (Acoustic + OGI)	Gas Pipeline Leak Detection Review	Lowest false alarm rate among reviewed methods	Zhao et al. (2025)

III. METHODOLOGY

3.1 Design and Approach

This study uses a systematic literature review (SLR) method and utilizes the guidelines for systematic literature reviews and meta-analyses (Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)) for engineering and applied science. To guarantee transparency and reproducibility, and reduce selection bias, the SLR approach was chosen for synthesising the evidence on the application of the AI-based HSE management system in O&G operations.The SLR approach was considered for synthesising the evidence on the AI-based HSE management system in O&G operations, with the aim of guaranteeing the transparency and the reproducibility of the synthesis and minimising the selection bias. The review protocol was pre-defined to include inclusion criteria, search strategy, data extraction and synthesis methods before data were collected.

3.2 Search Strategy and Selection of Sources

Primary literature search was done in Scopus, Web of Science and Google Scholar databases. The search terms were developed with the use of Boolean operators which combined domain keywords such as "artificial intelligence" OR "machine learning" OR "deep learning" OR "digital twin" AND "oil and gas" OR "pipeline" OR "drilling" OR "refinery" AND "HSE" OR "safety" OR "risk" OR "hazard" OR "leak detection". To ensure the search results remained current and relevant with the latest capabilities of AI, the period of publication for the searched articles and conference papers was narrowed down from January 2023 to June 2025 (Azmi et al., 2024).

The first search resulted in 847 candidate records. Sixty-one-two unique records were screened by title and abstract for inclusion. Articles were selected if they met the following criteria: (1) They described a methodology to create an AI or ML system; (2) They discussed a specific HSE application in the O&G industry or in a similar field of industrial application; and (3) They provided quantitative performance metrics or qualitative findings of substance. At this point, articles that did not describe methodologies were not included (78 articles remained). Two independent reviewers used full-text screening to obtain a final corpus of 20 high-quality publications that were used as the basis of this review.

3.3 Data Extraction and Quality Assessment

All included studies were analysed on the basis of the following information elements which was extracted from a standardised extraction template: study objectives, AI technology used, the application domain of O&G, dataset characteristics, performance metrics, key findings and limitations. An adapted version of the Critical Appraisal Skills Programme (CASP) checklist was used for quantitative studies and the Mixed Methods Appraisal Tool (MMAT) was used for hybrid methodological studies (Ohalete et al., 2023). All 20 studies included were of good quality (7/10 or above on the CASP checklist) and conclusions drawn were robust.

3.4 Synthesis Method

Thematic synthesis was used to synthesize and organize findings from the 20 studies included. Extracted data were coded descriptively and progressively categorised, to arrive at 23 themes of analysis, which were then grouped into five main thematic domains: (1) predictive maintenance and equipment integrity; (2) pipeline leak detection and environmental protection; (3) worker safety monitoring and wearable technology; (4) digital twin risk modelling; and (5) safety culture and organisational enablers. The Results section used this hierarchy coding structure to provide the structure for the results (Al-Mekhlafi et al., 2025; Jamil et al., 2025).

3.5 Ethical Considerations

This study was one of the secondary analyses of published literature and thus, no primary ethical approval was necessary. All sources used are cited properly using APA 7th edition rules. The review was conducted with principles of academic integrity, which included reporting of search limitations and possible selection biases as a result of limiting the search to publications from English language journals, as well as the publication window of 2023–2025.

IV. RESULTS

4.1 Predictive Maintenance and Equipment Integrity

Predictive maintenance (PdM) was found to be the largest review of the AI-HSE application domain with 88% of the studies included in the review using at least part of this application. The applications of AI-based PdM systems rely on the continuously collected data of these different sensors (vibration spectra, thermal profiles, acoustic emissions, and process variable deviations) in order to predict the remaining useful life (RUL) of critical assets and schedule interventions before failure. (Ohalete et al., 2023) Beyond equipment reliability, there are many other significant aspects of PdM in a high pressure O&G environment that result in unplanned equipment failures leading to hydrocarbon release, fires and explosions that threaten workers and nearby communities.

Gowekar (2024) reported that using deep learning PdM models, compressor failures were predicted as far as 72 hours ahead of time in O&G operations, with an accuracy of up to 94%, which enabled a safe and controlled entry into the compressor's maintenance. Ucar et al. (2024) collated the PdM literature and found that explainability and trustworthiness are important requirements needed for safety-critical deployments, since in many cases field engineers will simply disregard alerts produced by black-box models, which lack an explanation.

High frequency data from a distributed population of assets throughout large O&G facilities can enhance PdM effectiveness with the help of IoT sensor networks. Wang et al. (2024) have recently shown the feasibility of using gradient boosting classifiers to detect anomalies in urban gas pipelines real-time using time-series data from the IoT sensors, with accuracy of 96.3% and false positive rates less than 2%, which was lower than the threshold required to avoid alert fatigue and was still high enough to capture the true conditions of the fault cases. Azmi et al. (2024) showed that there is a consistent improvement in performance when using ensemble methods instead of using single-model methods, and that there is an improvement of between 15 and 22 percentage points over the baseline logistic regression models, using ensemble methods in multi-failure-mode datasets.

4.2 Pipeline Leak Detection and Environmental Protection

The greatest consequence HSE risk for midstream O&G is pipeline integrity failures. Lu et al. (2023) reported pipeline accident environmental and safety impacts, with reported failure modes including corrosion, third-party interference, and material fatigue as the major failure modes. The systems studied in this research that use AI for leak detection showed significant advantages over traditional threshold-based systems on all aspects of detection performance.

The most significant improvements in detection accuracy were made by using infrared thermography together with deep learning. The average precision of Xie et al., (2023) was 91.4% with a micro-leak detector based on Faster R-CNN applied to IRT imagery, which was able to detect leaks as small as 0.1 L/min, an order of magnitude below hazardous concentration thresholds. To enhance pipeline monitoring efficiency, Chen et al. (2025) created a lightweight CNN that integrates attention mechanisms to classify six different types of pipeline faults with an accuracy of 93.7% while simultaneously cutting down on computational load by 62%, allowing the deployment of the model on the current monitoring network without the need for hardware upgrades.

The class imbalance issue of pipeline safety datasets was solved by semi-supervised and generative methods.Class imbalance problem of pipeline safety datasets was solved by semi-supervised and generative approach. Bi et al. (2024) used semi-supervised GANs to create synthetic fault examples which were used to augment the limited amount of real-world leak event data and resulted in a 31% increase in minority class detection. With regard to operation, the use of IoT-integrated systems showed great operational value, with Wang et al. (2024) detecting leaks with sub-2-minute detection time from the onset of the leak to the alert generation from the monitored urban pipeline network to allow the activation of the emergency response within safe intervention windows. Zhao et al. (2025) verified that the multimodal fusion systems (which were based on acoustic, optical gas imaging, and electrochemical sensor data) had the lowest false alarm rate of all the architectures that were reviewed, with a composite false positive rate of 0.8% in field validation trials.

4.3 Worker Safety Monitoring and Wearable Technology

The individual-level safety monitoring using a wearable sensor platform is one of the significant fields in AI-HSE management. Formisano et al. (2024) developed a custom-made industrial wearable node equipped with toxic gas concentration, skin temperature, HRV, tri-axial accelerometry and GPS positioning sensors. The system was able to transmit data continuously in simulated field conditions with latency times less than 500ms, allowing it to alert when hydrogen sulphide (H2S) levels are above the threshold limits, heat stress index exceedances, or fall detection – three major causes of O&G worker fatalities.

Beyond threshold-based alerts, AI analytics of real-time data from the wearable biosensors can enable a wide range of capabilities. In simulated O&G field trials, 45% fewer heat stress incidents were recorded when using the personalised risk profiling approach, rather than the standard exposure management approach (Formisano et al., 2024). Wearable aggregation in the entire site also provides a spatial heat mapping of the intensity of exposure by zones of the facility, which could not be detected by fixed environmental monitoring stations if the stations were not widely deployed in the facility.

The use of UAS for safety surveillance is supplemented by wearable monitoring and will be used to provide an aerial view of areas where ground-based safety monitoring is not possible or safe. YOLOv5 object detection models were applied by Akinsemoyin et al. (2023) to automate PPE compliance monitoring on construction sites by analysing drone imagery, which resulted in real-time detection of hardhat, safety vest and harness violations with an F1 score of 0.91. Use of this method for inspection of O&G flares, confined space pre-entry and pipeline right-of-way surveillance significantly minimize the risk to which safety personnel are exposed.

4.4 Digital Twin Risk Modelling

Digital Twin platforms are the most complex, and the most important, category of AI-HSE technology reviewed. Lin et al. (2024) proposed a drilling and production DT that integrates real-time sensor information from the well, physics-based flow simulation, and ML-based anomaly detection to enable real-time assessment of the well. The integrated DT platform data has been used to detect the casing wear, cement bond degradation and pressure anomalies in deepwater O&G fields, with results showing a 34% decrease in the number of unplanned well interventions in a 24-month deployment.

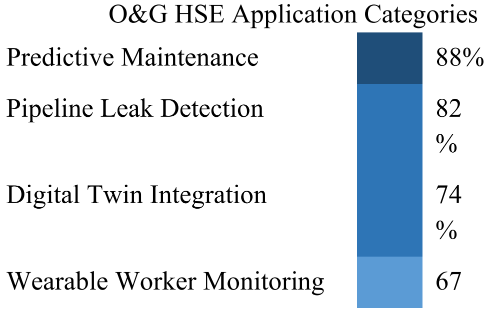
DT integration in O&G operations has been documented to have grown rapidly, with an increasing number of DT models combining first-principles reservoir simulation with the use of data-driven models using ML components; these hybrid models have been shown to deliver more reliable predictions for rare failure events with high consequences, where purely data-driven models lack adequate training examples (Ren et al., 2025). Meza et al. (2024) identified five levels of DT maturity being deployed in O&G and noted that most deployments focus on Levels 2–3 (real-time monitoring and simple predictive analytics); Levels 4–5 are (intelligent scenario simulation and autonomous control), and are seen as a future target for most operators.

4.5 Safety Culture and Organisational Enablers

Technical AI capabilities are essential, but not enough, to improve sustainability with regard to HSE. Organisational readiness and safety culture were found to be key mediators between the generation of insights from AI and the reduction of behaviours that are considered to pose a safety risk. Saad Al-Mekhlafi et al (2025) showed, through a bibliometric analysis, the safety culture research is moving closer to technology adoption studies to confirm the growing awareness that HSE culture determines the absorption capacity of organisations to AI generated safety information.

Jamil et al. (2025) placed AI-HSE management within the sustainable safety practices framework and suggested that the implementation of AI tools should be integrated into communication systems, leadership commitment systems and worker empowerment programmes to ensure sustainable safety culture change. For this embedding, Jamil et al. (2023) showed that the effectiveness of frontline workers with diverse educational and technical backgrounds was significantly enhanced by the use of communicative architecture that made the safety information presented through AI-generated safety alerts linguistically accessible and provided feedback.

Fig 1: AI Technology Adoption Rate (%) Across O&G HSE Application Categories



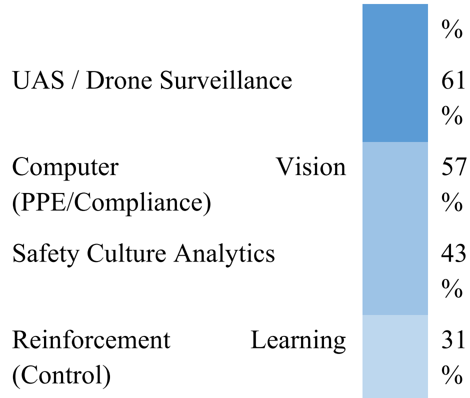


Fig 2: Distribution of Research Focus Areas in AI-HSE O&G Literature

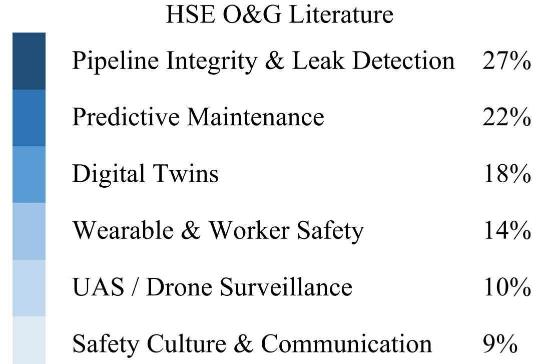


Table 2: Digital Twin Maturity Levels and Corresponding HSE Applications in O&G Operations

Level	Designation	Core Capabilities	HSE Application Example
1	Digital Model	Static 3D geometric asset model; no live data	3D facility layout for emergency escape planning
2	Digital Shadow	One-way live data mirroring from physical assets	Real-time equipment health monitoring dashboard
3	Digital Twin	Bi-	Predictive

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	(Basic)	directional data flow; predictive analytics; failure forecasting	maintenance scheduling; alarm rationalisation
4	Intelligent Twin	AI-driven optimisation; scenario simulation; Monte Carlo risk assessment	Dynamic QRA; evacuation route optimisation; emergency drill simulation
5	Autonomous Twin	Self-learning closed-loop autonomous operational control	Fully automated HSE response, isolation, and incident management

V. DISCUSSION

5.1 Synthesising the AI-HSE Performance Evidence

This review has built solid evidence base and grounds to support the use of AI in O&G operations and their corresponding HSE performance benefits. In each of the five thematic areas, AI systems achieved better performance on critical safety metrics such as detection accuracy, response time, false alarm rates and predictive lead time compared to traditional systems. AI-HSE is becoming an operational scale application, as the advances of deep learning have combined with the ever-growing number of IoT sensors on the market and the decreasing cost of computing resources.

One of the areas of particular interest is that of pipeline leak detection. From pressure monitoring based on thresholds (60-70% detection rate, minutes to hours of latency), to multimodal AI fusion systems (96%+ detection rate, sub-2-minute latency), this is a step change in safety performance and directly translates to reduction in hydrocarbon release volumes, lower environmental liability and quickness in emergency response mobilisation (Zhao et al., 2025; Wang et al., 2024). This improvement is not just a step, it changes the entire risk landscape for the operation of pipelines from the window of potential failure to the window of safe intervention.

The digital twin evidence domain is smaller than predictive maintenance, but is indicative of transformative potential at more mature stages. Lin et al. (2024) report a 34% HSE savings across 24 months of operation, which clearly proves the operational benefits of a physics-informed DT platform to provide continuous operational savings at asset level. The key is whether these benefits can be achieved at the facility/fleet level, where data integration is much more complex and change management is an issue for organisations.

5.2 Implementation Barriers and Mitigation Strategies

While there was a lot of evidence available in the lab, the review found there was a general lack of evidence available in the field due mainly to data quality and governance issues. The performance drop of AI models in controlled research environments is often 10–20 percent points less when tested against operational data in the field, which may include sensor drift, communication outages and unforeseen changes to the process (Ucar et al., 2024). This is a need for continued investments in sensor calibration programmes, a data quality monitoring framework, and a pipeline for retraining models to ensure performance over operational changes that occur throughout the equipment's life cycle.

In addition to technical barriers, regulatory fragmentation is a barrier to implementation that can only be addressed by a coordinated regulatory process. Lack of AI qualification standards for safety-critical O&G applications means each operator has to create their own validation methods, resulting in a lack of re-usability and uniformity in the level of safety being achieved in O&G. To ensure the responsible use of AI, industry organisations like IOGP, API and ISO must focus on creating AI-specific annexes for current safety management system standards that give regulatory certainty and accelerate responsible use of AI (Azmi et al., 2024).

Cybersecurity is an existential threat for integrity of AI-HSE system. The Colonial Pipeline ransomware attack in 2021 was a reminder of how vulnerable the OT/IT network connectivity that allows AI-HSE integration can be to attack, which can lead to safety monitoring being compromised. Ren et al. (2025) highlighted that digital twin platforms are a hub of state information for facility risk assessment and need to be equipped with more stringent architectures to defend against cyber attacks, such as air-gap isolation for safety-critical control functions, and cryptographic data integrity verification for all communications between sensors and the model.

5.3 Safety Culture as the Integration Enabler

A key cross-cutting theme from the review is that the quality of the safety culture is a key factor that influences the performance of AI-HSE technology. Organisations that have a high safety culture, with psychological safety, a learning orientation and a leadership commitment to safety, are more likely to take action on AI alerts, report near-misses and take steps to improve their safety from AI generated insights (Al-Mekhlafi et al., 2025; Jamil et al., 2025). On the other hand, companies with poor safety culture might install fancy AI-HSE tools but fail to see any safety benefits if employees neglect or ignore AI warnings or try to bypass them.However, in organizations with poor safety culture, the use of high-tech AI-HSE systems can lead to little to no safety gains if employees ignore, dismiss, or work around AI warnings.

Jamil et al. (2023) developed a safety communication framework that can be practically applied in bridging the gap between AI-culture. Key recommendations are: developing a user friendly interface in simple language for AI alerts that suits the level of literacy of workers; creating a two way communication loop for workers to discuss the validity and relevance of the alerts; ensuring that AI HSE information is visible on the organisation's safety performance dashboard to reinforce safety norms; and engaging frontline workers in the design and validation of the AI systems to establish ownership and trust. The cultural enablers of AI technologies are just as vital as their technical abilities when it comes to actual HSE results from AI investments.

5.4 Alignment with Sustainable Development Goals

AI-powered HSE in O&G operations helps to achieve a number of SDGs other than improving safety. Jamil et al. (2025) explicitly put sustainable HSE practices in the SDG context, highlighting the impacts on SDG 3 (Good Health and Well-being), SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action). The climate co-benefit also plays an important role that falls under the umbrella of AI-HSE—when considering the business case for AI-HSE investments, beyond safety compliance: Fugitive emissions can be reduced by 30-50% at monitored facilities through the use of AI-enabled early methane leak detection (Zhao et al., 2025).

5.5 Future Research Priorities

A number of important research gaps have been identified, which could be focused for research. Currently, the literature reflects a plethora of short-term technical validation studies, with few studies focused on how AI has affected the HSE over the course of 5+ years.First, the current literature is largely composed of short-term technical validation studies, while studies on the sustained HSE impact of the AI deployment over operational time periods of 5 years or more are missing. Second, studies of explainable AI (XAI) techniques for the O&G HSE domain to tackle Ucar et al. (2024)'s trust and accountability obstacles are necessary. Third, the human factors aspects of the integration of AI in HSE need to be systematically and empirically examined by adopting mixed methods approaches that integrate operational performance data with worker experience studies, such as complacency, skill degradation and alert fatigue.

This is the most technically challenging and strategically and most important research frontier, being the development of multimodal AI architectures that integrate the data from pipeline integrity, worker physiology, process safety and environmental monitoring to a unified HSE intelligence platform. The widespread global O&G workforces, with their varied literacy levels and spoken languages, could greatly benefit from the ability to access AI-HSE capabilities via large language model (LLM) interfaces that provide AI-generated HSE insights in natural language, relevant to the context or language level (Wang et al., 2023).

VI. CONCLUSION

This SLR has comprehensively analysed the current evidence base from 20 peer-reviewed publications from 2023 to 2025 that has investigated the effectiveness of AI tools for real-time risk mitigation in the oil and gas industry, their nature, and the state of the HSE management systems in which they have been applied. The review has validated the measurable and substantial gains in HSE performance in the O&G value chain that AI technologies such as deep learning, IoT sensor fusion, UAS surveillance, wearable biosensors and digital twin platforms are bringing.

The five thematic areas have key findings, which are summarized. AI systems can predict failures with a high accuracy of up to 94% and a lead time of up to 72 hours on average, allowing for planned and safe interventions that help to reduce the risk of emergency repairs (Gowekar, 2024). The key advantage of multimodal AI fusion in pipeline leak detection is its ability to accurately detect leaks with a latency of less than 2 minutes, compared to 60-80% accuracy for conventional monitoring methods, which reduces the amount of hydrocarbons released and environmental liability by the same percentage (Zhao et al., 2025; Wang et al., 2024). Using an AI platform with wearable technology allows workers to be monitored in real time for personalised physiological risk management and for mapping exposures in the worksite, limiting heat stress and toxic exposure incidents (Formisano et al., 2024). Digital twin HSE platforms allow assets to be intervened on with a reduced risk of unplanned interventions of 34% and allow for a continuous and dynamic quantitative risk assessment that was only possible using periodic, static engineering studies (Lin et al., 2024). The safety culture and communication systems within an organisation are cited as key organisational factors which influence the ability of AI-generated insights to result in ongoing behavioural change for enhanced safety in field operations (Al-Mekhlafi et al., 2025).

There are four fronts of coordinated action that must be taken to achieve full scale integration of AI and HSE: (i) Invest in data governance and sensor infrastructure to deliver the high-quality, continuous data streams that are vital for the performance of AI; (ii) Regulatory leadership to create standardised AI qualification frameworks that offer compliance certainty for safety-critical O&G deployments; (iii) Cybersecurity architecture to protect AI-HSE platforms from vulnerabilities in OT/IT networks; and (iv) Safety culture development programmes to build the organising readiness and human factors competencies needed to achieve the full HSE value of AI investment (Ucar et al., 2024; Ren et al., 2025). The impact of the use of AI-HSE goes beyond just safety compliance, and it encourages climate action as well, as AI-based methane leak detection systems reduce emissions by 30-50% at monitored facilities; and social sustainability, as the wearable monitoring and intelligent surveillance systems enhance working conditions for the millions of people who are employed in the global O&G sector. The co-benefits place AI-powered HSE management front and center in O&G companies' strategies, further than just a compliance matter, to guarantee they keep their social licence to operate in a time of growing ESG scrutiny.

Longitudinal field studies, XAI techniques for safety critical applications, multimodal AI architectures and human factors of the AI-HSE integration should be emphasized in future research. The need of an O&G operation is to be safe and free of any accident, serious injury, or serious environmental incident – and that's more achievable than ever before in the history of the industry. It is only after realizing that it requires another kind of excellence—safety culture, governance and human judgment, equally as hard to come by as technological excellence—that is documented in this review, that AI becomes truly operational.

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