

Conceptualizing the Impact of Organizational and Human Factors on Drilling Safety Performance: The Role of AI as a Moderator

*Ahmed Ali¹, Maniyarasi Gowindasamy¹, Noor Adila Abd. Raub²

¹Faculty of Business and Technology, University of Cyberjaya, Cyberjaya, Selangor, Malaysia

²Faculty of Business Management, Universiti Teknologi MARA Cawangan Puncak Alam, Selangor, Malaysia

Email: *afsali1@outlook.com, maniyarasi@cyberjaya.edu.my, adilaraub@uitm.edu.my

Corresponding Author: Ahmed Ali

Abstract: The oil and gas industry is one of the most complex and hazardous industries in the world, with operations that span across upstream, downstream, different environments, and countries. Drilling Activities are considered the most capital-intensive stage in the upstream oil and gas sector. Despite improvements in safety performance between 2018 and 2023, the International Association of Drilling Contractors (IADC) highlighted that the industry still faces challenges of incidents and their adverse financial impact. Previous studies have used incident causation methods to identify causes and various factors that lead to the accidents, a “reactive approach”. However, there is a gap in research that explores the numerical relation between Safety Performance and each of Human, Organization factors, and Artificial Intelligence (AI) through a quantitative approach. The research objective was to explore underpinning theories, identify incidents and their human and organizational factors in the industry, examine the impact of Artificial Intelligence on that relation, construct a Conceptual Framework that describes that relation, and develop robust control measures considering the AI to minimize chances of accidents in the industry. The research methodology will incorporate a stratified sampling mechanism, involving the distribution of questionnaires to 425 employees across various drilling crews within drilling companies in the Middle East. Both validity and reliability will be implemented, and hypotheses will be tested. The correlation between dependent and independent variables will be analysed using the quantitative method SPSS and AMOS for data visualization, concluding in the development of a comprehensive conceptual framework, and the best robust control measures will be driven qualitatively.

Keywords: *Artificial Intelligence, Human Factors, Organizational Factors, Safety Performance, Drilling Industry, Oil and Gas Sector*

1. Introduction and Background

The Oil and Gas industry faces numerous challenges and risks, such as fluctuating market prices, geopolitical uncertainties, environmental regulations, safety concerns, and social responsibility issues (Emeka-Okoli et al., 2024). It needs to constantly improve its performance in various aspects, such as technical efficiency, operational reliability, and HSE (Izaye, 2024). It is divided into three major sectors: upstream, midstream, and downstream (Patidar et al., 2023). Drilling is considered the most capital-intensive stage in the upstream oil and gas sector (Ochulor et al., 2024). The costs depend on many factors, such as the location, depth, and complexity of the reservoir (Sujan Kumar and Deivanathan, 2021), as well as the competitiveness and sustainability of the oil and gas industry (Ponomarenko et al., 2022). A simple drilling program can be divided into four main phases: site preparation and drilling completion (Allain et al., 2018). Site preparation Phase: This phase involves selecting and preparing the location, clearing the land, leveling, building access roads, moving the drilling rig and equipment from the old to the new location, installing utilities, and setting up a drilling rig and other facilities. This phase ends with spud-in and rig acceptance (“Oil and Gas Well Drilling and Servicing - Site Preparation,” 2018).

Drilling Phase involves using a drill bit attached to a drill string to create a hole in the earth's crust, reaching the target depth and location of the oil or gas reservoir. Drilling encounters challenges, such as rock hardness, pressure, temperature, stuck pipes, or fluid content (Fanchi and Christiansen, 2016).

Completion phase: This phase involves making the well ready for production by installing the final casing and cementing it to the wellbore, perforating the casing to allow the oil or gas to flow into the well, installing the production tubing, and stimulating or acidizing the rock formation (Flatem, 2021).

Problem Statement

The data is derived from the International Association of Drilling Contractors (IADC) Incident Statistics Program (ISP), as shown in Table 1, the total number of incidents reported from 2018 to 2023, along with the percentage change from the previous year, Total Recordable Injury Rate (TRIR), and Total Fatality Rate (FR).

Table 1: IADC Total Number of Incidents

Year	Incidents	% Change	TRIR	Total FR
2018	1,024	-	0.43	0.35
2019	1,132	10.5%	0.64	0.32
2020	1,264	11.7%	0.44	0.28
2021	1,321	4.5%	0.57	0.25
2022	1,356	2.6%	0.66	0.23
2023	1,389	2.4%	0.51	0.21

Source: IADC Safety performance data years 2018 and 2022 ("Safety performance indicators – 2018 data," 2019) ("Safety performance indicators - 2022 data," 2023)

The number of incidents reported in IADC increased steadily over the six years, with an average annual growth rate of 6.3% in columns 2 & 3. The highest percentage change was observed in 2020, when the number of incidents rose by 11.7% compared to 2019. This could be attributed to the impact of the COVID-19 pandemic, which disrupted the normal operations and safety protocols of the drilling industry. The lowest percentage change was observed in 2023, when the number of incidents increased by only 2.4% compared to 2022. This could indicate a stabilization of the trend or a result of improved safety measures and practices implemented by the IADC members. On the other hand, TRIR is a measure of the frequency of work-related injuries and illnesses per 200,000 working hours. Column 4 shows TRIR increased slightly over the six years, from 0.43 in 2018 to 0.51 in 2023. The Fatality rate is calculated as the number of fatalities per 100 million man-hours worked. Column 5 shows a steady decline in the rate over the years, indicating an improvement in the safety performance of the drilling industry. The rate of 2023 is projected to be half of the rate of 2018 (Carr, 2023). This suggests that despite the increase in the number of incidents reported, the severity of the incidents has been slightly increased but at a lower rate, or that the number of working hours has increased faster than the number of incidents. On average, TRIR fluctuates around 0.5.

Major Drilling and workover accidents

Several drilling-related incidents with significant consequences occurred last 10 years. A fire at a Pemex platform in April 2024 resulted in fatalities and injuries, impacting production by 200,000 bpd (barrels per day) (Čavčić, 2024). Another major platform fire at a Pemex facility in June 2023 caused deaths and affected production, with approximately 700,000 barrels impacted (Martinez, 2023). An Oklahoma drilling rig explosion in 2018, triggered by an uncontrolled gas release, led to fatalities (Wertz, 2018). The Baghjan oil well blowout and fire in 2020 in India caused casualties, environmental damage, and the displacement of more than 3000 families (Talukdar, 2021). An Argentine gas blowout in 2018 resulted in an uncontrolled release of gas and fluids due to a faulty valve, posing health and safety risks (Taillant, 2018). The Tamar gas platform fire in 2017 injured workers and damaged facilities due to a technical malfunction, disrupting gas supply and costing approximately \$100 million (Carpenter and Kostianoy, 2018). The Aliso Canyon gas leak (2015-2016) released substantial methane, leading to evacuations, health impacts, and an estimated cost of \$1 billion. It also had significant climate and air quality consequences (Choi et al., 2023). The biggest ever incident was the Deepwater Horizon blowout and explosion in 2010 resulted in the largest marine oil spill in history, causing extensive environmental damage and costing BP over \$65 billion. The incident was triggered by engineering failures and human errors that killed 11 workers and injured 17 others (Eisenberg and Adams, 2020).

In a nutshell, although there is an increasing use of technology in the drilling industry, many companies are still facing accidents that are reflected in TRIR. In the observed lack of research that explores the numerical relation between Safety Performance and each of Human, Organization, factors, and Artificial Intelligence through a

quantitative approach. The research takes its significance at three levels: at the Drilling Industry level through Enhancing Safety Standards, improving Efficiency and Productivity, contributing to Workforce Development and Skills Gap Analysis, Benchmarking and Technology Adoption. At the Company Level, it will help identify Targeted Safety Interventions in the organization, optimize AI Implementation to complement human capabilities and optimize organizational processes for maximum benefit and return on investment (ROI) and add Competitive Advantage by leveraging the positive effects of AI on safety performance. At the Workforce Level, by enhancing Situational Awareness, reducing Cognitive Load by automating routine tasks and providing decision support, Artificial Intelligence can free up mental capacity to focus on more complex tasks, personalize training, and Support and improve Safety Culture.

Research Questions

RQ1: How do organizational Factors influence safety performance in the drilling industry

RQ2: How do Human Factors affect safety performance in the drilling industry

RQ3: To what extent does AI moderate the relationship between Organizational Factors and safety performance in the drilling industry

RQ4: To what extent does AI moderate the relationship between Human Factors and safety performance in the drilling industry

Research Aim

To develop and validate a conceptual framework that examines the influence of organizational and human factors on safety performance in the drilling industry, while analyzing the moderating effect of AI on these relationships.

Research Objectives

RO1: To examine the effect of organizational factors on safety performance in the drilling industry.

RO2: To investigate the effect of human factors on safety performance in the drilling industry.

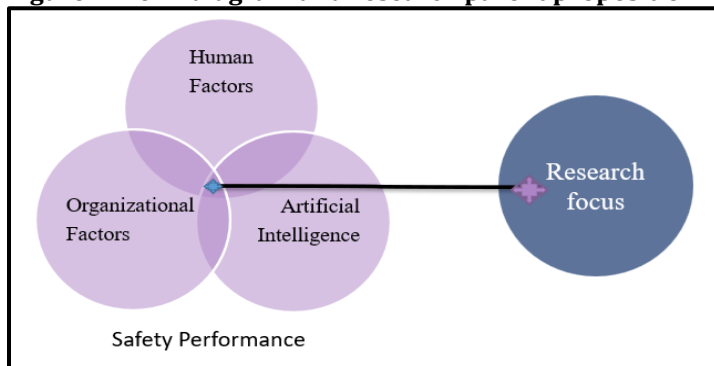
RO3: To analyze the moderating role of AI on the relationship between organizational factors and safety performance.

RO4: To analyze the moderating role of AI in the relationship between the human factors and safety performance.

2. Literature Review

The research process entailed collecting relevant data and statistics across multiple industries, and then the researcher focused on the oil and gas drilling sector to characterize the problem at hand. Additionally, the secondary literature review involves conducting online searches using relevant keywords to describe the parent categorical proposition in the research, as in Figure 1, according to Edwards (2004).

Figure 1: Venn diagram and research parent proposition



(Source: researcher's work)

- Parent 1: Artificial Intelligence
- Parent 2: Organizational Factors
- Parent 3: Human Factors,
- Parent 4: Safety Performance
- Research Focus

The above propositions combined in different ways to target and narrow the references by several search terms one after the other at each of the subsequent databases; the whole point of literature review is to say here is what the literature says and here is what it does not say and this is how the research is going to address those gaps, look at previous literature reviews, researcher used number of research engines, he wrote topic + literature review, or SLR “Systematic Literature Review” to explore a more comprehensive literature review, also he did his best to avoid too older paper to avoid not up to date information the focus was on last 3-5 years, for the older one he explored “Cited by” to get right UpToDate with what happening now.

Among the search engines used was Google Scholar (“Google Scholar Metrics Help,” 2024), OnePetro (“OnePetro,” n.d.), Elsevier’s ScienceDirect (“Open Access journals and books | ScienceDirect.com,” n.d.), The Bureau of Labor Statistics (BLS) (“History of the U.S. Bureau of Labor Statistics,” 2023), International Labor Organization (ILO) (“ILO Statistics and databases,” 2023). International Association of Oil and Gas Producers (“IOGP data,” n.d.), International Association of Drilling Contractors (“IADC.org,” n.d.), ASCE - American Society of Civil Engineers (“Home | ASCE,” 2023), EBSCOhost (“EBSCOhost Research Platform | EBSCO,” n.d.), UK HSE Executive Publications (“UK HSE Executive Health and safety statistics - HSE,” 2023).

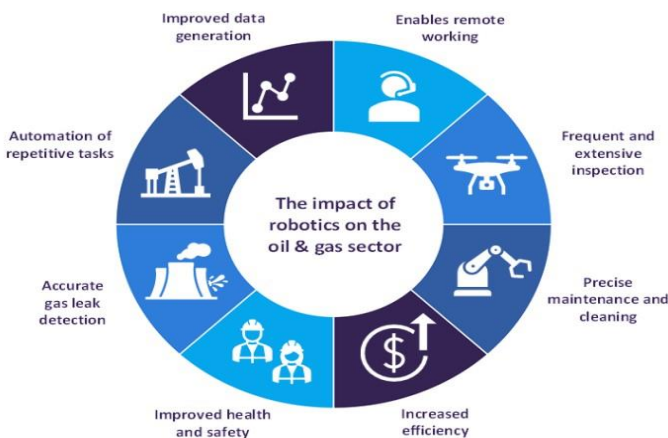
Safety Performance represents a critical component in this research (Figure 1) It is necessary to investigate the constituent elements that make up safety performance, as well as derive the interactions and interdependencies among the human, organizational, and Artificial Intelligence that affect Safety performance in the drilling industry.

Artificial Intelligence (AI)

AI, according to Davi (2023) refers to the capacity of computer systems to emulate human mental functions, this encompasses abilities such as learning knowledge from data, detecting patterns, and generating predictions, where AI can perform problem-solving through analyzing complex scenarios and devising solutions, often more quickly and precisely than humans. Also, AI can utilize data and reasoning to make informed choices, even in ambiguous situations. In terms of Decision-making.

While robotics has been an integral part of the oil and gas industry for several decades, the growing integration of digital technologies, such as AI, cloud computing, and the Internet of Things, has further diversified the applications of robots within the industry. According to Fernandes (2024), a significant number of robots, including terrestrial crawlers, quadrupeds, aerial drones, autonomous underwater vehicles, and remotely operated vehicles, are now being deployed in various oil and gas operations. These robots are utilized across the industry for a wide range of tasks, including surveys and material handling.

Figure 2: Impact of Robotics on the Oil & Gas Sector



Source: Global Data Thematic Research (Fernandes, 2024) AI Technologies in Drilling

Robots equipped with advanced technologies are yielding increasingly positive results in improving safety and efficiency within oil and gas operations. They are proving invaluable for executing complex tasks at production

facilities, thereby protecting workers from hazardous environments and reducing the likelihood of costly shutdowns. Their ability to perform repetitive and mundane tasks with minimal errors is saving time and internal resources for companies (Casal, 2023).

Hussain et al. (2024) explained in their book "Application of Artificial Intelligence in the Oil and Gas Industry" how the oil and gas industry utilizes various artificial intelligence technologies to enhance drilling operations. Machine Learning, a core component of AI, is employed for predictive modeling, pattern recognition, and automated decision-making. Deep Learning, a sophisticated subset of Machine Learning, excels at analyzing complex data such as images and sensor readings. Additionally, Natural Language Processing enables AI systems to comprehend and interpret human language, facilitating the analysis of drilling reports and unstructured data. Computer Vision technology allows AI systems to perceive and interpret images and videos, which is valuable for worker safety monitoring and automated inspection purposes.

AI and Drilling Optimization

Real-Time Data Analysis: AI algorithms can analyse vast amounts of drilling data from various sensors in real-time, identifying patterns and anomalies that humans might miss (Wood, 2024).

Predictive Modelling: By learning from historical data, AI can predict potential drilling anomaly problems like stuck pipe, equipment failure, pressure instability, or sudden fluid kicks, allowing for proactive mitigation, Hao et al. (2025) demonstrated how a predictive model significantly enhances the performance of Rate of Penetration (ROP) and drilling optimization.

Automated Drilling Control: Cao et al. (2025) explained how AI-powered systems can automate certain drilling parameters, such as weight on bit or drilling fluid properties, to optimize penetration rates and reduce non-productive time.

AI for Enhanced Safety in Drilling

Predicting and Preventing Accidents: through risk assessment, AI analyzes historical data, incident analysis, and root cause prediction (Khan et al., 2024), real-time sensor readings (like vibrations or pressure), and even weather forecasts to identify potential hazards before they escalate. And it can also trigger warning systems to alert for dangerous situations, giving crews time to evacuate or take corrective action (Hallowell and Spencer, 2024).

Improving Human Performance: because it can monitor human behavior, detect fatigue of individuals, and AI can analyze video feeds to detect signs of worker fatigue, a major contributor to accidents. Javay et al. (2024) in their pilot project demonstrated how the AI algorithm can detect certain equipment or parts on the rig floor along with their motions and foresee their movement, and compare against the predefined condition to determine an unsafe condition or behavior of the workforce.

Safety Performance

Measuring Safety Performance

Measuring organizational performance serves crucial strategic purposes because it allows companies to thoroughly assess their current position, providing a comprehensive understanding of their strengths, weaknesses, and areas for improvement (Walhekar and Khatke, 2020) this, in turn, enables organizations to track their progress over time, identify meaningful trends, and set targeted, data-driven objectives (Mitrea-Curpanaru, 2021), guides more informed budgeting decisions and benchmarking against competitors (Purwoko et al., 2023).

Safety performance is evaluated through the assessment of supervisors and worker-level metrics. (Ketola et al., 2002) proficient safety management is widely acknowledged to generate substantial financial advantages by lowering accident-related costs (Caldarescu et al., 2021). Effective safety management can likewise enhance organizational productivity and financial performance (Šolc et al., 2022) and even lead to a competitive advantage (Fernández-Muñiz et al., 2009).

The discussion of safety performance became more advanced than only focusing on "lagging" indicators (Jääskeläinen et al., 2022), Organizations focus on lagging indicators measuring past events, such as accident reports, which capture the lack of safety rather than its existence. This approach is not ideal for driving improvements, as a low accident rate does not necessarily indicate that risks are effectively managed,

particularly in companies where the likelihood of accidents is low but significant hazards persist (Tremblay and Badri, 2018).

According to Podgórski (2015), safety performance can be defined as the degree to which an organization achieves its safety goals and objectives and prevents or minimizes the occurrence and consequences of adverse events. Safety performance can be measured using different indicators, such as leading or lagging indicators; both have their advantages and limitations.

Leading indicators

Leading indicators are proactive measures that reflect the inputs and processes of safety management. (Bayramova et al., 2023). Golabchi et al (2024) defined leading indicators as measurable factors that provide information about the current state of safety and health performance, and can be used to forecast future outcomes, but he did not provide an exhaustive list of leading indicators, as these can vary depending on nature of the work, location among other factors etc., he categorized leading indicators by their focus into Organizational Leading indicators represented in compliance assurance and Operational Leading indicators could be measured through number of indicators such frequency of adherence to Personal Protective Equipment (PPE).

Lagging indicators

It is reactive measures that reflect the outcomes of incidents. According to Niu et al., it can provide objective and reliable data on the safety performance, but they may not reflect the underlying or contributing factors of accidents. Therefore, a balanced and comprehensive approach is needed to measure safety performance, using a combination of leading and lagging indicators, and taking into account the different levels and dimensions of safety performance.

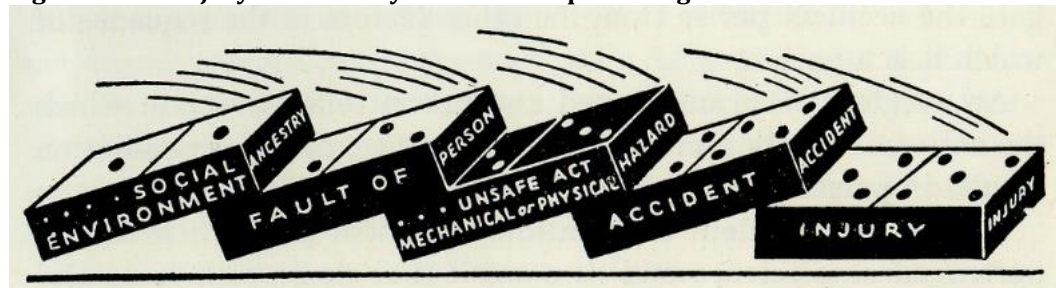
Underpinning Theories

The field of accident causation analysis and safety performance has a rich and extensive history that researchers have dedicated years to studying the different factors that contribute to accidents across diverse industries and domains (Leveson, 2004).

Domino theory

Heinrich (1931) developed the "domino theory" that shows an accident as a sequence of a causal chain of events, represented by dominoes that topple once the first block falls, as in Figure .

Figure 3: The injury is caused by the action of preceding factors



Source: The domino model of accident causation, as depicted by H. Heinrich in the 1950 edition of his book *Industrial Accident Prevention: A Scientific Approach* (Marsden, 2017).

However, if this sequence is disrupted by eliminating even one of the contributing factors (Figure), the injury can be prevented, as illustrated in (. Figure) below:

Figure 4: The unsafe act and mechanical hazard. the central factors in the accident sequences

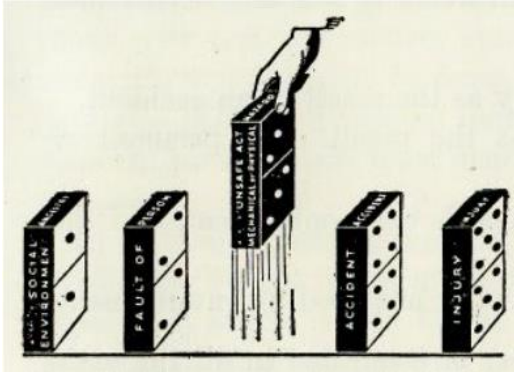
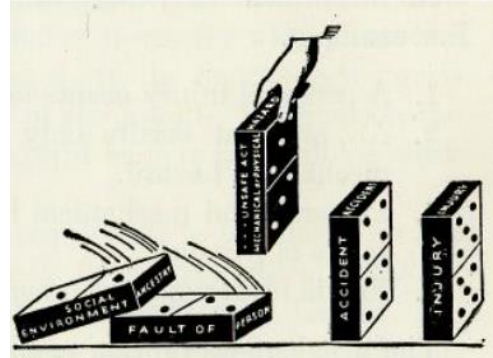


Figure 5: The removal of the central factor makes the action of preceding factors ineffective.



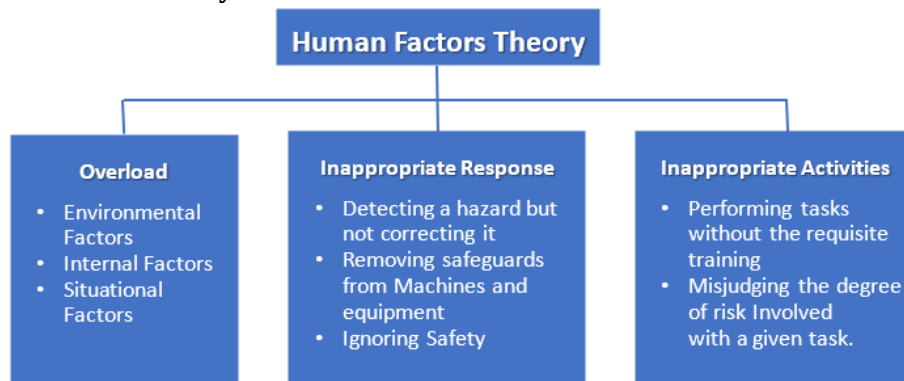
Source: (Marsden, 2017)

It was groundbreaking for its time, according to Erbayat. (2024) It has several disadvantages, such as oversimplification of causation into a linear cause-and-effect relationship and emphasis on individual capability as if it focuses on Individual Blame.

Human Factors theory

Wagenaar et al. (1990) explained Ferrell's Human Factors theory in terms of accidents often resulting from human error, and can be attributed to three key elements: overload, inappropriate response, and inappropriate activities, as per the following Figure , Radhakrishna (2015) clarified how it emphasizes the importance of a "systematic" approach to integrating human capabilities and limitations into the design of equipment, environments, and processes.

Figure 6: Human Factors Theory



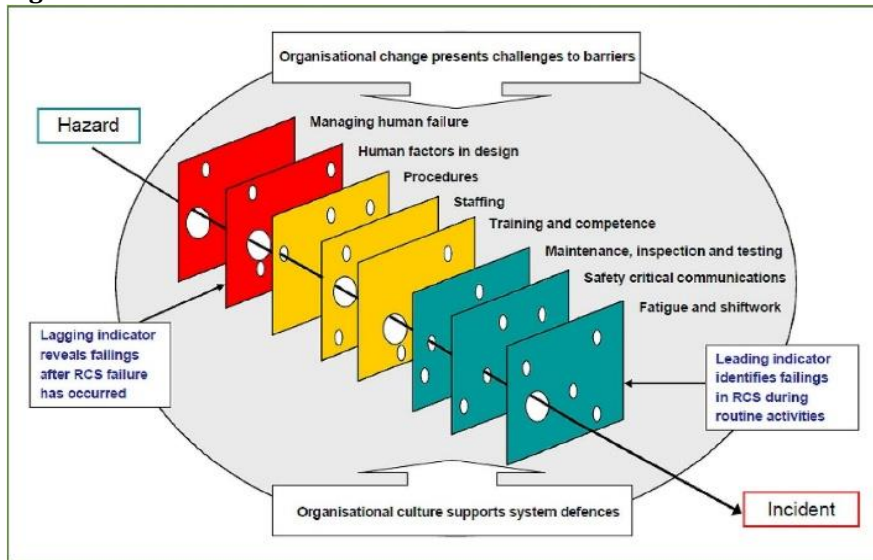
Source: (Mannan, 2014)

Limitations of HC Theory include the inability to predict rare events, Shapiro (2003) explained that over-reliance on past data only may fail to interpret novel situations or emerging technologies. HC theory is associated with Implementation Challenges in terms of cost and Time Constraints. Organizations might encounter resistance to change due to budget limitations or operational disruptions (Rouse et al., 1991).

Swiss Cheese Model

The Swiss Cheese Model was initiated by Reason (1990) and then became a widely used model for understanding how accidents occur in complex systems. Swiss cheese consists of slices lined up; each slice represents a layer of defense in a system, such as safety procedures, equipment safeguards, or human vigilance. The holes in the cheese represent weaknesses or failures in these defenses.

Figure 7: Swiss Cheese Model



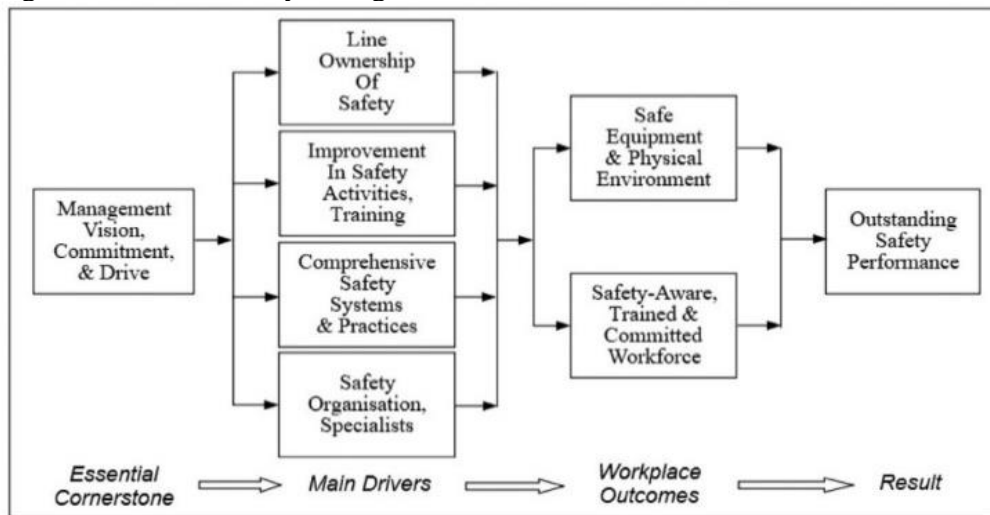
Source: (Gonyora and Ventura-Medina, 2024)

When holes align, hazards pass through and cause harm. Hollnagel (2016) argues that when these barriers are functioning effectively, the likelihood of accidents is reduced. Drawbacks when oversimplifying the complex and multifaceted nature of accident causation by portraying it as a sequential chain of failures. However, real-world accidents often involve intricate interrelationships and feedback mechanisms among various factors (Hollnagel, 2016). Leveson (2016) explained in actual scenarios, identifying all potential weaknesses, failures, and defects in every layer of defense is not static and can be challenging over time.

System theory

Stewart (2001) developed his accident model, Safety Management Model, using System Theory, in which accidents don't have singular causes but result from the complex interplay of factors within a system, showing humans as part of the system, interacting with equipment, tasks, and the work environment. According to the Figure He outlined that to achieve an outstanding safety performance, it starts with management vision, commitment, and drive. Challenges are represented in complexity, data requirements, and Organizational resistance.

Figure 8: Model of Safety Management based on Accident Causation Model



Source: (Stewart, 2001)

Variables Identification

In statistical studies, Stewart (2024) outlined that understanding variables is crucial for designing experiments, analysing data, drawing meaningful cause-and-effect relationships, formulating hypotheses, and making informed decisions based on empirical evidence.

Independent Variables

In human and safety-related research, an independent variable is the factor that is proposed to influence or bring about changes in safety-related outcomes (Sigall and Mills, 1998).

Organizational Factors (OFs), Components of IV

Haber et al. (1990) at a nuclear power plant examined the influence of organizational factors on safety performance was examined and highlighted several key organizational factors that impact safety, such as standardization of procedures, decision-making processes, supervision, Risk Assessment, management attention, and organizational culture.

Risk Assessment and Safety Performance: Risk assessment is a crucial process for improving safety performance. Pillay (2015), after reviewing twenty academic articles, suggested that in high-risk sectors, such as construction, mining, and healthcare, there are some advancements in comprehending the causation of accidents and developing effective risk assessment.

Supervision and Safety Performance: Effective supervision plays a pivotal role in cultivating a strong safety culture and improving overall safety performance within organizations, according to Chih et al. (2017) where supervisors play a critical role in delivering onsite safety training in terms of safe work practice, mentoring workers, and offering guidance while his/her subordinates are doing the task (Rabenu, 2021).

Awareness / Training / Competency: Awareness, training, and competency are fundamental pillars of a strong safety culture, and they play a vital role in enhancing safety performance. (Felix Orikipte and Raphael Ejike Ewim, 2024). According to Ferguson (2021) Workers must be aware of potential hazards linked with their tasks and the significance of following safety procedures, and effective training programs equip workers with the necessary knowledge and skills to perform their jobs safely.

Job Method / Planning: Hislop (1999) in his book "Construction Site Safety: A Guide for Managing Contractors," pointed out that well-defined job methods and thorough planning are essential for ensuring safe work practices and improving overall safety performance. Desrochers (1994) explained that incorporating principles of risk reduction into the job planning process can yield significant improvements in safety performance.

Permit to Work System: Jusoh et al. (2020) have proven that Permit to Work elements have a significant impact on occupational accidents, where hazardous activity has become the main element that affects occupational accidents; accident in hazardous activity contributes about thirty percent of the occupational accidents in the Petrochemical Plant. The Permit to Work process ensures that appropriate control measures, such as isolating energy sources, are implemented before work begins, thereby enhancing safety (Maddox et al., 1991).

Audits and Inspections: The Canadian Centre for Occupational Health and Safety has identified the importance of workplace inspections in preventing incidents, injuries, and illnesses, because through a critical examination of the workplace, inspections help to capture and record hazards, enabling corrective action, part of Health and safety committees duties is to assist in planning, conducting, reporting, and monitoring these inspections, therefore regular workplace inspections are a crucial component of the overall occupational health and safety program and management system, if present (CCOHS, 2024).

The above review clearly proves the direct relationship between organizational factors and safety performance in the drilling industry and answers the Research Objective 1 (RO1) "the effect of organizational factors on safety performance in the drilling industry".

Human Factors (HFs), Components of IV

Unsafe Position / Posture incidents and safety performance: According to the Construction statistics in Great Britain 2024 report, work-related musculoskeletal disorders (MSDs) are the primary cause of nonfatal occupational injuries in the construction industry, with an estimated 40,000 workers suffering from a work-related musculoskeletal disorder, which is 52% of all ill health in this sector, based on the average estimate over 2021/22-2023/24 (Benson, 2024). Lortie & Pelletier (1996) explained that awkward or sustained

postures, particularly when combined with repetitive motions or forceful exertions, can directly cause musculoskeletal disorders such as back injuries, sprains, and strains

Impact of Failure to Secure Safety Performance: Peatie et al. (2024) investigated falling objects incidents and found that unsecured tools, materials, or debris falling from heights can strike workers or cause damage below, representing a major cause of injuries and fatalities on construction sites. In his study of the impact of dropped objects on offshore (Floating, Production, Storage and offloading tankers - FPSO) Ozguc, (2021) found that unstable structures and failure to secure structural elements, scaffolding, or formwork can lead to collapses, posing a serious risk to workers and the asset.

Failure to follow procedure and safety performance: Instances where established safety protocols, work instructions, or standard operating procedures are not adhered to can be described as "procedure not followed", Isa et al. (2021) found that this deviation from prescribed practices can have significant detrimental impacts on safety performance. Praino and Sharit (2016) explained situations when workers do not follow procedures; they may be exposed to hazards they are unprepared for, increasing the likelihood of accidents and compromising safety systems, because procedures are often integral to the proper functioning of safety systems; therefore, deviations from established procedures can undermine the effectiveness of these systems, elevating the risk of incidents.

Perkinson (2018) highlighted that when procedures are not followed, it can be challenging to determine the root causes of accidents, hindering efforts to prevent similar incidents in the future and leading to inaccurate incident investigation. Inconsistent Outcomes were highlighted by Hale and Borys (2013) that failure to adhere to procedures can lead to variable results, making it challenging to identify and address safety issues efficiently, consequently, leading to erosion of safety culture, where procedures are not consistently followed can foster complacency, increase risk-taking behaviors and decrease both safety performance and weaken the overall safety culture.

Impact of Inadequate Communication on Safety Performance: In the article of Naji et al. (2022) the abbreviation "Inadequate communication" is normally used to refer to insufficient, unclear, or ineffective exchange of information between individuals or teams involved in a task or project. In safety-critical environments like the oil and gas industry, inadequate communication can have severe consequences. It could lead to an increased risk of accidents as Zahed (2024) highlighted in his research the risk of aviation incidents due to factors such as miscommunication between pilot and air traffic control.

Lack of Attention and Accidents: Aroke's research in (2022) has demonstrated that work experience, safety training, and personality traits like conscientiousness, agreeableness, and openness to experience are significantly linked to visual attention and improved hazard identification ability; these findings have significant implications for enhancing safety performance.

In their study Muley and Wang (2024) employed a wearable eye-tracking device to examine the influence of personality traits on construction workers' recognition of fatal near-miss scenarios under different levels of stress. Their findings revealed significant differences in workers' visual attention between stressful and non-stressful conditions, indicating that workers demonstrated decreased attentiveness under stress.

Impact of taking shot cuts on Safety Performance: Saed and Omar (2024) studied lessons learned from the aviation industry to adopt in the oil and gas sector. They found that taking shortcuts, or finding ways around deficiencies, such as when pieces of equipment or tools are missed, mechanics use inappropriate tools, or adjust equipment designed for a different purpose to maintain workflow, regardless of the procedures set by organizations. The preceding review provides clear evidence of a direct relationship between human factors and safety performance in the drilling industry, thereby addressing Research Objective 2 (RO2) "effect of human factors on safety performance in the drilling industry".

Dependent Variables

The essence of the research is to comprehend how the independent variable impacts the dependent variables, which embody the safety-related outcomes related to previously elaborated components of the independent variable under investigation.

Safety Performance (SPs), Components of DV

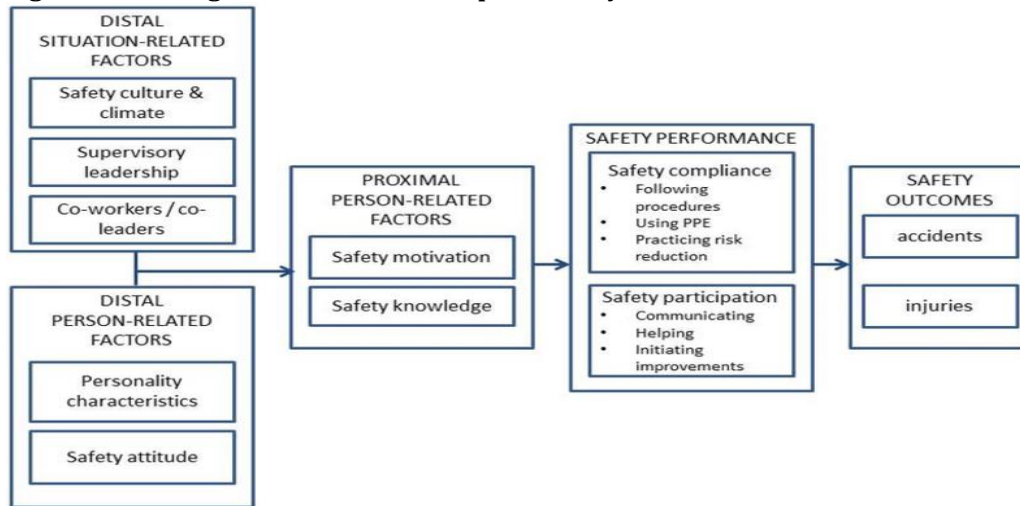
Safety Performance may be used to refer to two different concepts: a) metrics for safety outcomes, such as the number of injuries per year, as explained in lagging indicators, and b) metrics for safety-related behaviours of individuals (Burke et al., 2002).

The first order factors for injuries are: 1) Fatal Accident Rate (FR) and 2) Total Recordable Injury Rate (TRIR). In contrast to safety performance behaviors, safety outcomes are tangible events or results, such as accidents, injuries, or fatalities. But the metric safety behaviors, according to Neal and Griffin (2006) in the workplace, safety entails two distinct components: safety compliance and safety participation.

Safety Compliance with procedure

Conceptualizing safety performance in terms of safety compliance can be scaled by the frequency with which employees engage in the behaviors and are distinguishable in terms of not wearing PPE as required. (Burke et al., 2002). Several conceptual models of safety performance have been developed, such as the model outlined by Burke et al. (2002) in Figure .

Figure 9: An integrative model of workplace safety



Source: (Christian et al., 2009)

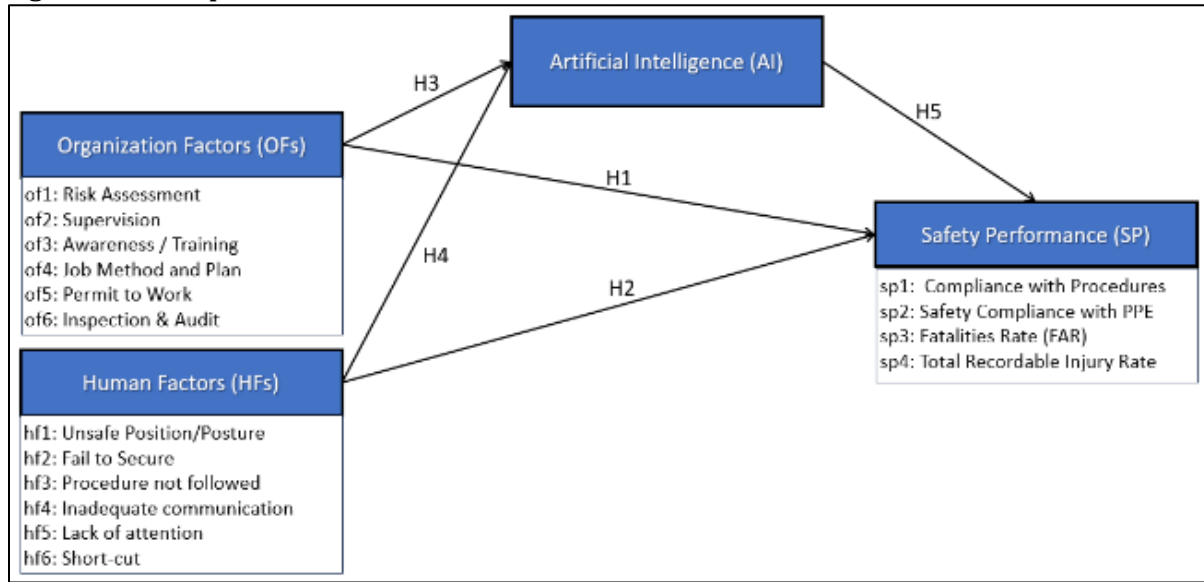
Compliance with PPE

Xian et al. (2022) in recent study pointed out that the key predictors of safety performance are the presence of adequate barriers for hazards and risks, the compliance of wearing Personal Protective Equipment (PPE) on-site, and the frequency of conducting toolbox meetings.

Moderating Factors (MV): Artificial Intelligence

Artificial Intelligence as a moderating variable, in a study conducted by Liu (2022), showed that artificial intelligence involves the creation of machines capable of performing tasks that typically require human-level intelligence. These tasks encompass learning, problem-solving, decision-making, speech recognition, and visual perception. AI systems are designed to analyze data, identify patterns, and make predictions or decisions based on the information they process. According to Solanki et al., (2022) there are various approaches to AI, including machine learning, deep learning, and rule-based systems. AI has found widespread applications across numerous industries, from healthcare and finance to transportation and manufacturing.

Figure 10: Conceptual Framework of the research, Source: Researcher's work



Conceptual Framework for the research

The literature review found that organizational and human factors significantly impact safety performance in upstream oil and gas drilling. Theories suggest a correlation between these factors and safety outcomes. The research will investigate how AI could moderate or mediate the impact of organizational factors, such as enhancing risk assessment, improving supervision, and automating permit systems. Also, will investigate how the AI could mediate or moderate the impact of human factors, such as detecting unsafe behaviours and monitoring compliance, then produce the entire Conceptual Framework of the research, as in the following figure.

Hypothesis development

The research considers three relationships: the first relation is a direct path between the IV (OFs) toward DV (SP) and IV (HFs) toward DV (SP); the second relation is an indirect path between IVs and DV, where AI penetrates the link as a mediator, as in Figure , while the third relation AI will act as a moderator between IV (OFs) toward DV (SP) and IV (HFs) toward DV (SP) to assess how the AI influences the nature, direction, or strength of the relation between IVs and DV. Consequently, the following hypothesis will be examined:

H1: Organization Factors can significantly improve the safety performance

H2: Human Factors can significantly improve the safety performance

H3: Artificial Intelligence plays a mediator role in the relationship between Organization Factors and safety performance.

H4: Artificial Intelligence plays a moderator role in the relationship between Human Factors and safety performance.

H5: Artificial Intelligence improves the safety performance

3. Research Methodology

The researcher used a mixed-method approach, and his design includes two phases to validate the conclusion that can inform more strategic decision-makers in the industry. It is essential to tell the reader that this paper discusses only the results of Phase one and Phase two will be elaborated in a separate paper.

Phase one

Focuses on analyzing primary data from incident reports, quantitatively determining the common organizational and human-related causes contributing to 80% of the incidents (Nowobilski and Hoła, 2023). This analysis helps identify the key areas that require immediate attention and prioritization; in addition, it helps validate the independent variables.

Phase two

Using survey questionnaires tailored to interview the drilling crew. Two lists of survey questionnaires were developed, the first includes closed-ended and demographic questionnaires for quantitative analysis and assessing the hypotheses and conceptual framework. The second list includes demographic and open-ended questionnaires, where the responses will be analyzed qualitatively to gain in-depth insights into the crew's perspectives and experiences. Incorporating both open and closed question types will allow the researcher to leverage the advantages of each approach (Semyonov-Tal and Lewin-Epstein, 2021).

Development of Questionnaires and Pilot Study

After collecting relevant questionnaires, the researcher will review them in one or more pilot studies to ensure they address the aim and objectives. The filtration process could remove some irrelevant questions related to working at height activities.

Population

Considering an estimated population size of approximately 8,712 employees in the company at the beginning of the research, the study requires a minimum sample size of 424 individuals who meet the inclusion criteria as explained in the 0 Sampling Size.

Sampling Method

A stratified sampling mechanism was selected because stratification requires that characteristics of the population members be known, so that the population can be stratified first before selecting the sample. (Bickman and Rog, 2008) It means that specific characteristics of individuals (e.g., different positions at the rig site) are represented as per the following:

- | | | | |
|----|--|----|---|
| 1 | Rig manager | 2 | Assistant Rig Manager |
| 3 | Rig Mechanic | 4 | Rig Electricians |
| 5 | Field safety engineer | 6 | Driller day/ Night shifts |
| 7 | Derrick-men | 8 | Barge Engineer offshore |
| 9 | Roustabouts from the day and Night shift | 10 | Floor-men |
| 11 | Assistant Driller | 12 | Labor foremen onshore or crane operators offshore |

Sampling Size

Cochran's (1978), sample size formula was used to determine an appropriate and representative sample size. The following equation provides the formula for calculating sample size, considering an estimated population size of approximately 8,712 employees in the drilling company with a 95% confidence level and at least 5 percent—plus or minus—precision: The Cochran formula is:

$$n_0 = \frac{Z^2 pq}{e^2}$$

n_0 = sample size, e = e is the desired level of precision (i.e., the margin of error) = 5%

p = estimated proportion of an attribute that is present in the population, 0.5 is the maximum variability, $q = 1 - p$, Z = abscissa of the normal curve that cuts off an area α at the tails ($1 - \alpha$ equals the desired confidence level, i.e., 95%) = 1.96

Sample Size Calculation = $(1.96)^2(0.5)(0.5) / (0.05)^2 = 385$ copies of questionnaire. A 10% allowance is provided to account for those who do not participate but subsequently drop out (non-response rate and incomplete responses). The study requires a minimum sample size of 424 individuals who meet the inclusion criteria. ("Sample Size in Statistics," 2017).

Ethical Clearance

Ethics are in accordance with the university requirements; all interviews are adults; the study will not include any misleading or incomplete information.

Reliability

Reliability (or consistency) means the stability of a measurement scale, i.e., how far the interview will give the same results on separate occasions (Bannigan and Watson, 2009). In this research, the 1st pilot interview tests were conducted, followed by fine-tuning the list of questions, then the 2nd pilot interview tests were conducted

by asking the same rig crew members the same questions twice by two different interviewers (an independent Third-party contractor and a Field Safety Engineer), where the higher the coefficient, the more stable and reliable result of the interview (Polit and Beck, 2004). Cronbach's alpha (α), a perfectly adequate index, the reliability of the research instruments will be higher when the value of Cronbach's alpha (α) is closer to 1.00 (Othman et al., 2022). Generally, values of Cronbach's alpha (α) (Nunnally, 1978):

- less than 0.60 is considered to be poor,
- those in the 0.70 range are considered acceptable, and
- Those over 0.80 are considered to be good

Validity

Charlton (2000) highlighted the importance of a pre-test and pilot study, and it cannot be eliminated, also the resultant modifications to the questions will increase the validity, reliability and responsiveness of a questionnaire, she argued that the validity of the feedback obtained from survey questionnaires rely on the extent to which the author, who write the questions communicate their intended meaning to interviewers, who in turn convey the questions' meaning to respondents. During the interviews, the third-party contractor may be introduced to explain every question in detail in case the respondent has any doubts about the meaning. Furthermore, in this research, the researcher may do a 2nd pilot test to make sure questions are clear, and there is no confusion at any of them.

4. Results

This section presents the Pareto-Lorenz analysis method and sets of results relating to only phase 1: Quantitative Method for statistical analysis of accidents' causes. Since there are many Human Factors and Organizational Factors actually contributing to incidents, and to avoid complications, the researcher used Pareto-Lorenz (Hoła et al., 2018). To analyze and identify the most contributing factors. The Pareto-Lorenz ABC analysis, or simply ABC analysis, is a widely utilized business management technique for inventory categorization and control. It is grounded in the Pareto principle, which suggests that approximately 80% of outcomes can be attributed to 20% of the contributing factors (Robinson, 1983).

Pareto-Lorenz ABC Analysis Method

Every accident is caused by at least several causes. In the analysis method for the first phase, the causation of an accident was assumed as all deficiencies, inadequacies, and irregularities related to:

- Human (H) or employees and their behavior,
- Organization factors (O) at the workplace
- And Technical (T), which includes materials or equipment factors, we call it technical

Therefore, the set "P" of all causes of accidents is the sum of the subset representing the technical causes "T", a subset of the organizational list of causes "O", and the subset of human causes "H". The value of "P" is defined in equation 1;

Equation 1: $P = T \cup O \cup H$

Under each T, O, H set, there are several causes listed in equation 2;

Equation 2: $T = \{t_k \mid k = 1, 2, 3, \dots, K\}$, $O = \{O_m \mid m = 1, 2, 3, \dots, M\}$, $H = \{h_n \mid n = 1, 2, 3, \dots, N\}$

In this research Pareto-Lorenz ABC method (Hoła et al., 2018) of analysis will be used, according to the ABC method (Chu et al., 2008). It is necessary to divide the causes from the set into three subgroups. It was assumed that:

- The set of important causes, designated as A, forms a list of causes that account for 80% of all the causes that are attributable to a particular cause group. In the discussion, the researcher will focus on them
- The set of less relevant causes, designated as B, forms a list of causes that account for 15% of all the causes that are attributable to a particular cause group, and will not be part of the discussion.
- The set of irrelevant causes, designated as C, forms a list of causes that account for 5% of all the causes identified in the set.

ABC classification is proposed to identify the list of causes with the greatest importance. The calculation method is a universal calculation using Excel software; it applies to the analysis of each one in the three groups of causes of accidents involving (H, O, T). Steps of the analysis are summarized in:

- Defining detailed specific causes and their cardinalities (corresponding values) in the analyzed generic group. This information is presented as a sequence of ordered pairs of numbers (p_x, a_x) , where p_x ($x = 1, 2, \dots, X$) (represents the identified details of causes and a_x indicates the number of occurrences of the examined cause in the analyzed subset H, O, or T.
- Organizing sequences of pairs of numbers (p_x, a_x) That describes the analyzed causes in descending order. The position of a pair in the ordered sequence is determined by the number of occurrences of an attribute. p_x in the subset T, O, or H according to the rule in equation 3,

Equation 3: **if** $a_{x+1} \geq a_x$, **then** $p_{x+1} < p_x$

- Calculate the percentage share u_x of occurrences of the cause p_x In the total of all examined causes according to the following formula:

Equation 4: $u_x = \frac{a_x}{\sum_{x=1}^X a_x} \cdot 100\%$

Calculate the percentage of the cumulated sum of subsequent causes according to the following formula, in equation 5

Equation 5: $S_x = \sum_{i=1}^x u_x \quad x = 1, 2, 3, \dots, X.$

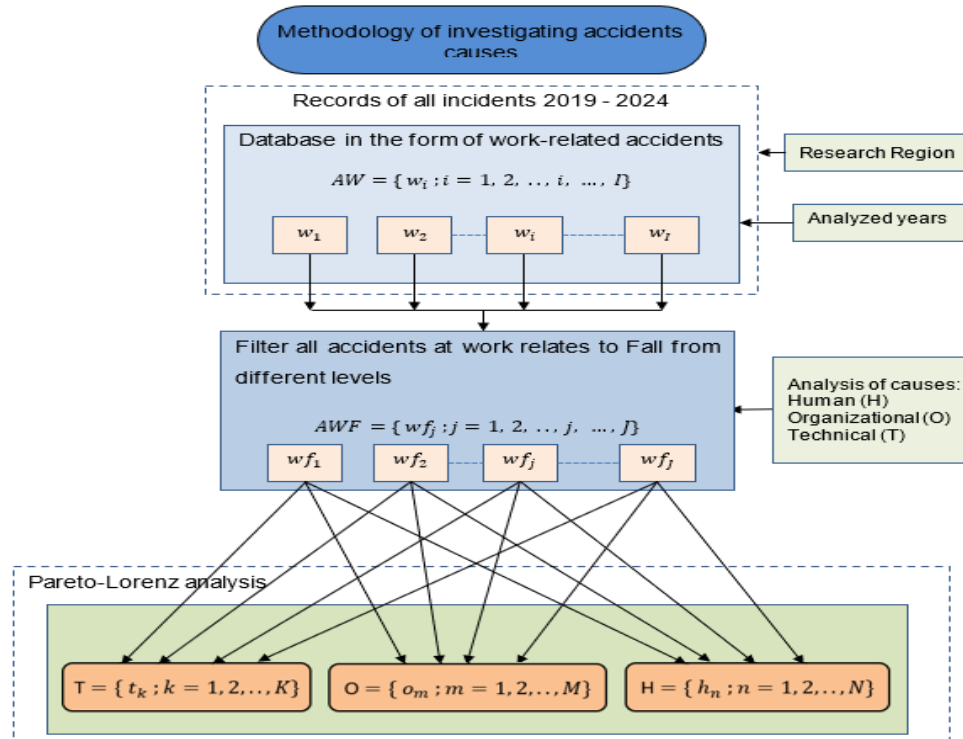
- Defining the affiliation of specific causes to one of the valid classes to classify causes according to the degree of their influence on the occurrence of an accident,

The proposed methodology of classifying and evaluating the validity of causes of accidents involving personal injury is presented in the following figure. The direct source of information on the course of all types of incidents, including HIPO near-miss, was an incident management system < 3550 > events (AW) during the period (2019 – 2024), w_i - an incident event (single event) i , which occurred during five years 2019 – 2024, $I = 3550$, where: $AW = \{w_i; i = 1, 2, \dots, i, \dots, I\}$

A detailed analysis of recordable accidents during the same period wf_i (LTI, MTO, RWC, FTL)

$AWF = \{wf_j; j = 1, 2, \dots, j, \dots, J\}; \quad S_x = \sum_{i=1}^x u_x \quad x = 1, 2, 3, \dots, X.$

Figure 11: Methodology of classifying accident investigation causes

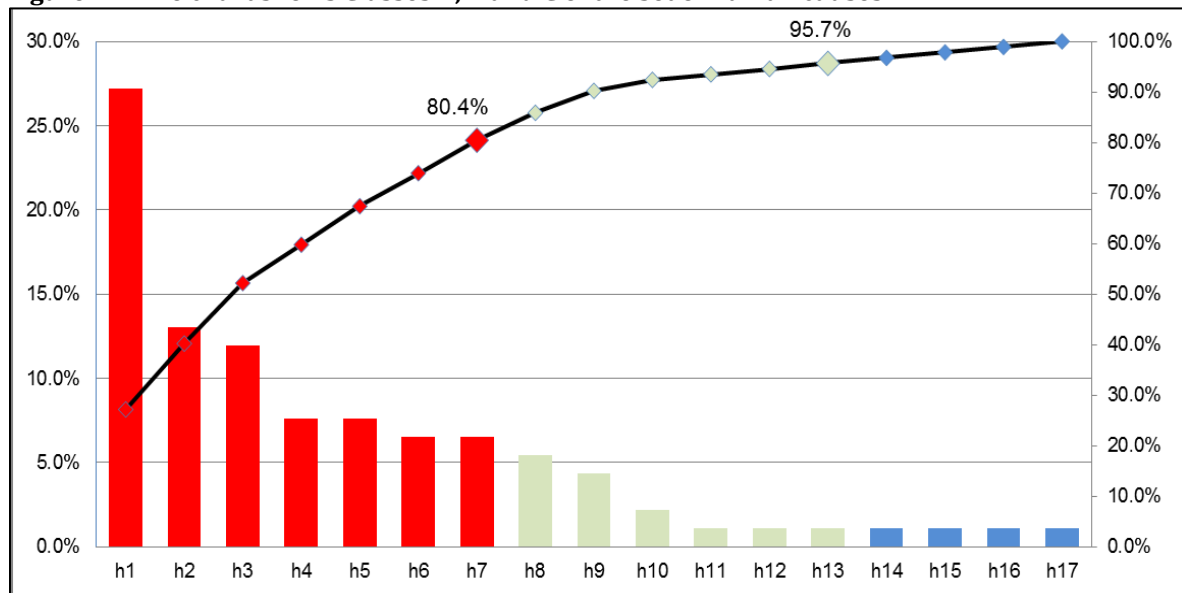


Source: (Hoła et al., 2018)

Table 2: Human (H) Subset of Causes (Source: Researcher's work)

Human Factor	Type of Human (H) Subset of Causes	The cardinality of the Occurrence of H	Share Ux (%)	Cumulative Share Sx (%)	Validity Class
hf1	Unsafe Position / Posture	25	27.2%	27.2%	A
hf2	Fail to secure	12	13.0%	40.2%	A
hf3	Procedure not followed	11	12.0%	52.2%	A
hf4	Inadequate communication	7	7.6%	59.8%	A
hf5	Lack of attention	7	7.6%	67.4%	A
hf6	Short-cut	6	6.5%	73.9%	A
hf7	Failure to use the STOP action	6	6.5%	80.4%	A
hf8	Overconfidence / Complacency	5	5.4%	85.9%	B
hf9	Inadequate judgment	4	4.3%	90.2%	B
hf10	Failure to use the right anchor point	2	2.2%	92.4%	B
hf11	Inadequate Use of Protective Methods	1	1.1%	93.5%	B
hf12	Inadequate work speed	1	1.1%	94.6%	B
hf13	Intentional violation	1	1.1%	95.7%	C
hf14	Lack of Focus / Memory Failure	1	1.1%	96.7%	C
hf15	Operating at an improper speed	1	1.1%	97.8%	C
hf16	Start Activity without PTW	1	1.1%	98.9%	C
Sum of Cardinalities of Human Occurrence		92	100.0%		

Figure 12: The chart shows Classes A, B and C of the set of human causes

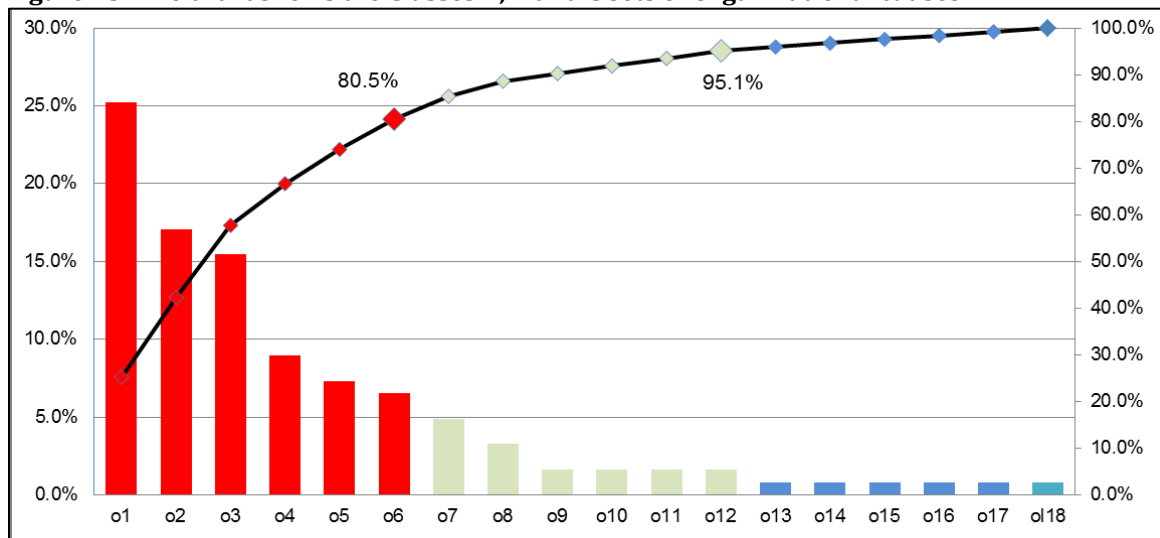


Source: Researcher's work

Table 3: Organizational (O) Subset of Causes

Org. Factor	Type of Organizational (O) Subset of Causes	cardinality of Occurrence of (O)	Share Ux (%)	Cumulative Share Sx (%)	Validity Class
of1	Inadequate Risk Assessment (JSA, TRA, Check Card)	31	25.2%	25.2%	A
of2	Inadequate Supervision	21	17.1%	42.3%	A
of3	Lack of Awareness / Training / Competency	19	15.4%	57.7%	A
of4	Inadequate job Method	11	8.9%	66.7%	A
of5	Inadequate Job Plan	9	7.3%	74.0%	A
of6	Inadequate Inspection / Audit	8	6.5%	80.5%	A
of7	Inadequate housekeeping	6	4.9%	85.4%	B
of8	Failure to warn	4	3.3%	88.6%	B
of9	Improper implementation of the PTW system	2	1.6%	90.2%	B
of10	Improper lifting practice	2	1.6%	91.9%	B
of11	Inadequate Procedure	2	1.6%	93.5%	B
of12	Stress / Tire	2	1.6%	95.1%	B
of13	Crew under time pressure	1	0.8%	95.9%	C
of14	improper handover	1	0.8%	96.7%	C
of15	Inadequate Implementation of MOC	1	0.8%	97.6%	C
of16	No toolbox talk	1	0.8%	98.4%	C
of17	Procedure does not exist	1	0.8%	99.2%	C
of18	Unclear or conflicting assignment of responsibility	1	0.8%	100.0%	C
Sum of Cardinalities of Organizational Occurrence		123	100.00%		

Figure 13: The chart shows the Classes A, B and C sets of Organizational causes



Source: Researcher's work

Discussion

Here, the researcher shed light on the top three factors under Human and Organization factors and how Artificial Intelligence has the optional to show a reduction in accidents and better safety performance.

Organizational Factors and AI

As in Causes Factors such as “Inadequate Risk Assessment - Job Safety Analysis JSA, Task Risk Assessment TRA, Check Card” contribute the maximum, followed by “Inadequate Supervision”, “Lack of Awareness / Training / Competency”, then “Inadequate job Method/plan” and “Inadequate Inspection / QC /QA”. The organizational factors have the most significant share of causes (123/251=49%). Risk Assessment and Safety Performance: where conducting robust risk assessments is a critical process for enhancing safety performance, both Hudson and Stephens (2000) Highlighted that effective risk assessment can yield several beneficial outcomes by proactively identifying hazards before incidents occur, better resource allocation, and, in a recent literature review on the construction industry, Kalidass et al. (2023) Highlighted that Artificial intelligence has the potential to significantly enhance risk assessment and improve safety performance in several ways.

For Risk assessment, as it is the most contributing factor in accidents, this result is in line with the recent literature review on the construction industry, Kalidass et al. (2023) explained that AI has the potential to significantly enhance risk assessment and improve safety performance in several ways; such as: i) automate certain aspects of the risk assessment process in terms of hazard identification and consequence analysis, freeing up human resources for more complex task, ii) AI algorithms can analyze large datasets of safety information, including incident reports, near misses, and sensor data, to identify patterns and trends that might not be apparent to human analysts, iii) AI can be used to develop predictive models that forecast the likelihood of future incidents based on historical data and current conditions.

Similarly, for the second most contributing organizational factor (Supervision), the experimental results of Rongrong et al.,(2020) supports the researcher where AI has the potential to complement and enhance the role of supervision in several ways: i) Real-Time Monitoring and Alerts: AI-powered systems can monitor work activities in real-time, using data from sensors, cameras, and wearable devices, and can detect unsafe behaviors or conditions, enabling timely interventions, ii) Data-Driven Insights: AI can analyze large datasets of safety information to identify trends, patterns, and high-risk areas, helping supervisors focus their attention and resources on the most critical areas. iii) Automated Reporting and Documentation: AI can automate tasks such as incident reporting, safety inspections, and training records, freeing up supervisors to concentrate on more proactive safety management activities. iv) Performance Monitoring and Evaluation: AI can track worker performance related to safety, providing supervisors with objective data to identify areas for improvement and deliver targeted feedback. Also, Hickert et al. (2023) add v) Remote Supervision and Support: AI-powered tools can facilitate remote supervision by providing real-time information and communication channels, particularly in geographically dispersed work environments.

Moving to the third most contributing organization factor (Lack of Awareness / Training / Competency), the AI has the potential to significantly enhance safety training and competency development, leading to improved safety performance in several ways: i) personalized training; AI-powered algorithms can customize training programs for individual workers based on their specific job roles, experience levels, and learning preferences, Albaladejo-González et al. (2024) Explained how a personalized approach can enhance training effectiveness and knowledge retention, they demonstrated the ability of Artificial Intelligence to forecast students' achievement in online educational settings by evaluating the breadth and calibre of trainee engagement in learning endeavors, such as discussion forums.

He preceding review elucidated the moderating influence of Artificial Intelligence on the relationship between organizational factors and safety performance in the drilling industry, thus addressing Research Objective 3 (RO3) “analyze the moderating role of AI in the relationship between the organizational factors and safety performance in the drilling industry”.

Human Factors and AI

As in Table 2 Human(H) Subset of Causes after implementation of the (H, O, T) causation method revealed that total cardinalities = 251 (sum of Human, Organizational, and Technical, respectively 92, 123, and 36). The total share of human factor = $92/251 \times 100\% = 37\%$ of the entire list of causes. Analysis of human factors as shown in showed Injured Person's (IP) “Unsafe Position / Posture” was the most contributing human cause, then the “failure of IP to use/secure PPE: i.e., full body harness, “Failure to follow Procedure, “Inadequate Communication,” and “Lack of attention”.

Unsafe position/posture is the highest case under human factors, Mei et al. (2024) presented how artificial intelligence can automatically detect and manage guardrail climbing behavior and workers' unsafe posture in construction sites, by using existing surveillance cameras, the system can be deployed at low cost with minimal interference with workers, and the detection of their unsafe behavior, which could lead to falls from height.

Failure to secure refers to neglecting to properly fasten, stabilize, or restrain objects or equipment in the construction environment. This led to some accidents happening; oversight can have significant impacts on safety performance. Image recognition capabilities can enable artificial intelligence systems to analyze visual data from construction site cameras or drones, identifying unsecured objects or equipment and alerting workers or supervisors to potential hazards, according to the recent study by Durlik et al., (2024).

Third contributing factor, when workers not following the procedure, this case will be challenging to the artificial intelligence because it could be complicated, not straight forward considering the ideal scenario of work site which in most cases different than reality, however we need to understand that where procedures are not consistently followed can fostering complacency, increase risk-taking behaviors and decrease both safety performance and weaken the overall safety culture. This area opens the door to Artificial Intelligence use cases in the near future.

The preceding review explained how Artificial Intelligence moderates the relation between human factors and safety performance drilling industry, thereby addressing Research Objective 4 (RO4) "analyze the moderating role of AI in the relationship between the human factors and safety performance in the drilling industry".

5. Managerial Implications and Recommendations

Human Factors and AI addressing unsafe positions/postures using AI-driven video analytics offers a cost-effective solution, minimizing risks, failure to secure scenarios by identifying unsecured objects, and prompting immediate alerts. For instances of workers not following procedures, AI applications are complex due to real-world deviations from ideal scenarios, necessitating comprehensive machine learning about the details of every procedure and developing a proof of concept for each use case. Organizational Factors and AI: AI enhances risk assessment by automating hazard identification, analysing safety data for trends, and predicting incidents. AI-driven real-time monitoring, data analysis, and automated reporting augment supervision, improving safety management. AI also revolutionizes safety training through personalized programs tailored to individual needs and performance. Managerial Implications and Recommendations are expected to cover:

- Prioritize AI Implementation in High-Risk Areas: Focus on AI deployment in areas prone to falls and unsecured equipment incidents to maximize safety impact.
- Develop Adaptive AI Systems: Create AI algorithms that can adapt to the dynamic nature of different drilling rig layouts, and ensure all blind spots are covered.
- Invest in Comprehensive Safety Data Collection: Establish robust systems for collecting and analysing safety data to inform AI models and improve predictive capabilities.
- Enhance Supervisory Oversight with AI: Equip supervisors with AI-driven tools for real-time monitoring, data analysis, and automated reporting to improve safety management.
- Personalize Safety Training Programs: Utilize AI to customize training programs, addressing individual needs and performance gaps to enhance knowledge retention and safety performance.

Conclusion

The research successfully covered the main questions, identified organizational and human factors that account for the majority of accidents in the drilling industry. It outlined the most common artificial intelligence solutions that could address the primary causes of accidents and examined the underpinning theories that correlate with the research's focus area.

The first phase of the research methodology was completed, using Pareto-Lorenz, the researcher analysed accident records to identify that 20% of the causes attributed to 80% of the incidents. The research also identified independent and dependent variables and successfully constructed a Conceptual Framework for the effect of Artificial Intelligence on Safety Performance in the Drilling Industry.

However, the second phase of the research is still in progress, and it is anticipated to develop Conceptual Framework of the research, validate the hypotheses and will be published in another paper, in which the results of quantitative and qualitative surveys will be analysed through SPSS and visualized through AMOS software; then, hypotheses will be validated along with elaborated discuss for the results.

Reference

- Albaladejo-González, M., Ruipérez-Valiente, J.A., Gmez Mármol, F. (2024). Artificial Intelligence to Support the Training and Assessment of Professionals: A Systematic Literature Review. *ACM Comput Surv*, 57(29), 1-56. <https://doi.org/10.1145/3699712>
- Allain, M.O., Dyson, M., Jing, X., Pentland, C., Polikar, M., Suicmez, V.S., (2018). *Imperial College Lectures In Petroleum Engineering, The - Volume 4: Drilling and Reservoir Appraisal*. World Scientific. <https://books.google.ae/books?id=pdWEDwAAQBAJ>
- Aroke, O.M. (2022). *Measuring Attention, Working Memory, and Visual Perception to Reduce the Risk of Injuries in the Construction Industry* (PhD Thesis). George Mason University. <https://search.proquest.com/openview/0449427f445ae7ad789c62355239e6a7/1?pq-origsite=gscholar&cbl=18750&diss=y>
- Bannigan, K., Watson, R., (2009). Reliability and validity in a nutshell. *J. Clin. Nurs.* 18, 3237–3243. <https://doi.org/10.1111/j.1365-2702.2009.02939.x>
- Bayramova, A., Edwards, D.J., Roberts, C., Rillie, I., (2023). Constructs of leading indicators: A synthesis of safety literature. *J. Safety Res.* <https://doi.org/10.1016/j.jsr.2023.04.015>
- Benson, P., (2024). *Construction statistics in Great Britain, 2024 (Annual statistics)*. UK Health and Safety Executive. <https://www.hse.gov.uk/statistics/industry/index.htm>
- Bickman, L., Rog, D.J. (2008). *The SAGE Handbook of Applied Social Research Methods*. SAGE Publications. ISBN: 1412973317, 9781412973311. [https://books.google.com/books?hl=en&lr=&id=DBIPDQAAQBAJ&oi=fnd&pg=PR13&dq=Fanchi,+J.R.,+Christiansen,+R.L.,+\(2016\).+Introduction+to+Petroleum+Engineering.+John+Wiley+%26+Sons.&ots=alyNaHtiML&sig=NAaMMLLvIP0QLIGb1aMmop26wbl](https://books.google.com/books?hl=en&lr=&id=DBIPDQAAQBAJ&oi=fnd&pg=PR13&dq=Fanchi,+J.R.,+Christiansen,+R.L.,+(2016).+Introduction+to+Petroleum+Engineering.+John+Wiley+%26+Sons.&ots=alyNaHtiML&sig=NAaMMLLvIP0QLIGb1aMmop26wbl) (accessed 10.12.23).
- Burke, M.J., Sarpy, S.A., Tesluk, P.E., Smith-Crowe, K. (2002). General Safety Performance: A Test of a Grounded Theoretical Model. *Pers. Psychol.* 55, 429–457. <https://doi.org/10.1111/j.1744-6570.2002.tb00116.x>
- Caldarescu, G., Florea, L., Nagit, G., Bernevig, M.-A., (2021). The importance of performance indicators in occupational safety and health management-a review. *MATEC Web Conf.* 343, 10016. <https://doi.org/10.1051/mateconf/202134310016>
- Cao, J., Gocmen, E., Nabavi, J., Oedegaard, S.I., Kristiansen, T.G., Khosravianian, R., Solem, K. (2025). Optimizing Drilling Operations in Real-Time: The Role of Digital Twins in Reducing Risks and Enhancing Performance. <https://doi.org/10.2118/223819-MS>
- Carpenter, A., Kostianoy, A.G. (2018). Conclusions for Part II: National Case Studies, in: Carpenter, A., Kostianoy, A.G. (Eds.), *Oil Pollution in the Mediterranean Sea: Part II, The Handbook of Environmental Chemistry*. Springer International Publishing, Cham, pp. 263–285. https://doi.org/10.1007/698_2018_362
- Carr, K., (2023). Incident Statistics Program's 2022 Annual Report Now Available. IADC.org. URL <https://iadc.org/drillbits/incident-statistics-programs-2022-annual-report-now-available/> (accessed 12.2.23).
- Casal, A., (2023). PSM Evergreening with Artificial Intelligence, in: Abu Dhabi International Petroleum Exhibition and Conference. <https://doi.org/10.2118/216445-MS>
- Čavčić, M., (2024). Fire at Gulf of Mexico platform ends in fatality, while multiple workers suffer injuries. *Offshore Energy*. URL <https://www.offshore-energy.biz/fire-at-gulf-of-mexico-platform-ends-in-fatality-while-multiple-workers-suffer-injuries/> (accessed 6.9.24).
- CCOHS, (2024). Effective Workplace Inspections [WWW Document]. *Can. Cent. Occup. Health Saf.* URL <https://www.ccohs.ca/oshanswers/prevention/effectiv.html> (accessed 12.1.24).
- Charlton, R., 2000. Research: Is an 'Ideal' Questionnaire Possible? *Int. J. Clin. Pract.* 54, 356–359. <https://doi.org/10.1111/j.1742-1241.2000.tb11922.x>
- Chih, Y.-Y., Kiazad, K., Cheng, D., Lajom, J.A.L., Restubog, S.L.D., (2017). Feeling Positive and Productive: Role of Supervisor–Worker Relationship in Predicting Construction Workers' Performance in the Philippines. *J. Constr. Eng. Manag.* 143, 04017049. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001346](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001346)

- Choi, A., Kim, P., Park, A. (2023). The effects of air quality on housing prices: Evidence from the Aliso Canyon gas leak. *J. Hous. Econ.* 62, 101966. <https://doi.org/10.1016/j.jhe.2023.101966>
- Christian, M.S., Bradley, J.C., Wallace, J.C., Burke, M.J. (2009). Workplace safety: a meta-analysis of the roles of person and situation factors. *J. Appl. Psychol.* 94, 1103. <https://psycnet.apa.org/doi/10.1037/a0016172>
- Chu, C.-W., Liang, G.-S., Liao, C.-T., (2008). Controlling inventory by combining ABC analysis and fuzzy classification. *Comput. Ind. Eng.* 55, 841–851. <https://doi.org/10.1016/j.cie.2008.03.006>
- Cochran, W.G. (1978). Laplace's Ratio Estimator, in: David, H.A. (Ed.), *Contributions to Survey Sampling and Applied Statistics*. Academic Press, pp. 3–10. <https://doi.org/10.1016/B978-0-12-204750-3.50008-3>
- Desrochers, Y.P. (1994). Focus on risk management and job planning: The key to preventing workplace fatalities. *Electr. Today Can.* 6:3. <https://www.osti.gov/etdeweb/biblio/7205881> (accessed 1.23.24).
- Durlik, I., Miller, T., Kostecka, E., Tuński, T., (2024). Artificial Intelligence in Maritime Transportation: A Comprehensive Review of Safety and Risk Management Applications. *Appl. Sci.* 14, 8420. <https://doi.org/10.3390/app14188420>
- EBSCOhost Research Platform | EBSCO [WWW Document], n.d. URL <https://www.ebsco.com/products/ebscohost-research-platform> (accessed 12.4.23).
- Edwards, A.W.F. (2004). *Cogwheels of the Mind: The Story of Venn Diagrams*. JHU Press. (accessed 12.27.23).
- Eisenberg, J., Adams, A. (2020). OFFSHORE DRILLING. <https://www.nrdc.org/sites/default/files/offshore-drilling-coastline-risk-fs.pdf> (accessed 6.8.24).
- Emeka-Okoli, S., Nwankwo, E.E., Nwankwo, T.C., Otonnah, C.A., (2024). Navigating Non-Technical Risks in The Oil & Gas Industry: Insights and Frameworks Review. *Int. J. Appl. Res. Soc. Sci.* 6, 348–359. <https://fepl.com/index.php/ijarss/article/view/892>
- Erbayat, C.K., (2024). Investigation of nonlinear interactions causing the major coal mine accidents in Türkiye using system dynamics modeling (Master's Thesis). Middle East Technical University. <https://open.metu.edu.tr/handle/11511/109797> (accessed 1.25.25).
- Fanchi, J.R., Christiansen, R.L. (2016). *Introduction to Petroleum Engineering*. John Wiley & Sons. [https://books.google.com/books?hl=en&lr=&id=DBIPDQAAQBAJ&oi=fnd&pg=PR13&dq=Fanchi,+J.R.,+Christiansen,+R.L.,+\(2016\).+Introduction+to+Petroleum+Engineering.+John+Wiley+%26+Sons.&ots=aLyNaHtiML&sig=NAaMMLLviP0QLGb1aMmoP26wbl](https://books.google.com/books?hl=en&lr=&id=DBIPDQAAQBAJ&oi=fnd&pg=PR13&dq=Fanchi,+J.R.,+Christiansen,+R.L.,+(2016).+Introduction+to+Petroleum+Engineering.+John+Wiley+%26+Sons.&ots=aLyNaHtiML&sig=NAaMMLLviP0QLGb1aMmoP26wbl) (accessed 1.20.24).
- Felix Orikpete, O., Raphael Ejike Ewim, D. (2024). Interplay of human factors and safety culture in nuclear safety for enhanced organizational and individual Performance: A comprehensive review. *Nucl. Eng. Des.* 416, 112797. <https://doi.org/10.1016/j.nucengdes.2023.112797>
- Ferguson, A. (2021). Artificial intelligence and on-the-job safety | Safety+Health magazine [WWW Document]. Saf. Health. URL <https://www.safetyandhealthmagazine.com/articles/22026-artificial-intelligence-worker-safety> (accessed 11.29.24).
- Fernandes, A. (2024). Robotics in Oil and Gas - Strategic Intelligence.
- Fernández-Muñiz, B., Montes-Peón, J.M., Vázquez-Ordás, C.J. (2009). The relation between occupational safety management and firm performance. *Saf. Sci.* 47, 980–991. <https://doi.org/10.1016/j.ssci.2008.10.022>
- Flatem, R. (2021). Defining Completions [WWW Document]. Schlumberger Transform. Technol. Defin. Complet. URL <https://careers.slb.com/inside-slb/transformation-technology/defining-completions> (accessed 6.8.24).
- Golabchi, H., Abellanosa, A.D., Lefsrud, L., Pereira, E., Mohamed, Y., (2024). A comprehensive systematic review of safety leading indicators in construction. *Saf. Sci.* 172, 106433. <https://doi.org/10.1016/j.ssci.2024.106433>
- Gonyora, M., Ventura-Medina, E. (2024). Investigating the relationship between human and organizational factors, maintenance, and accidents. The case of the chemical process industry in South Africa. *Saf. Sci.* 176, 106530. <https://doi.org/10.1016/j.ssci.2024.106530>
- Google Scholar Metrics Help [WWW Document], (2024). URL <https://scholar.google.com/intl/en/scholar/metrics.html#overview> (accessed 11.23.24).
- Haber, S.B., Metlay, D.S., Crouch, D.A. (1990). Influence of Organizational Factors on Safety. *Proc. Hum. Factors Soc. Annu. Meet.* 34, 871–875. <https://doi.org/10.1177/154193129003401211>
- Hale, A., Borys, D., (2013). Working to rule or working safely? Part 2: The management of safety rules and procedures. *Saf. Sci.* 55, 222–231. <https://doi.org/10.1016/j.ssci.2012.05.013>
- Hallowell, M. R., Spencer, C. (2024). Safety Classification & Learning Model: Defining & Classifying Potential Serious Injuries & Fatalities. *Prof. Saf.* 69, 18–26. <https://onepetro.org/PS/article->

- abstract/69/02/18/540787/Safety-Classification-amp-Learning-Model-Defining?redirected
From=fulltext (accessed 12.3.24)
- Hao, J., Xu, H., Peng, Z., Cao, Z. (2025). An online adaptive ROP prediction model using GBDT and Bayesian Optimization algorithm in drilling. *Geoenery Sci. Eng.* 246, 213596. <https://doi.org/10.1016/j.geoen.2024.213596>
- Heinrich, H.W. (1931). *Industrial Accident Prevention: A Scientific Approach*, McGraw-Hill Insurance Series. McGraw-Hill Book Company, Incorporated. <https://books.google.ae/books?id=mPZAAAAIAAJ> <https://www.bls.gov/bls/history/home.htm> (accessed 10.3.24)
- Hickert, C., Li, S., Wu, C. (2023). Cooperation for Scalable Supervision of Autonomy in Mixed Traffic. *IEEE Trans. Robot.* 39, 2751–2769. <https://doi.org/10.1109/TRO.2023.3262120>
- Hislop, R.D. (1999). *Construction Site Safety: A Guide for Managing Contractors*. CRC Press.
- History of the U.S. Bureau of Labor Statistics : U.S. Bureau of Labor Statistics [WWW Document], 2023. URL <https://www.bls.gov/bls/history/home.htm> (accessed 12.4.23).
- Hoła, A., Sawicki, M., Szóstak, M. (2018). Methodology of Classifying the Causes of Occupational Accidents Involving Construction Scaffolding Using Pareto-Lorenz Analysis. *Appl. Sci.* 8, 48. <https://doi.org/10.3390/app8010048>
- Hollnagel, E. (2016). *Barriers and Accident Prevention*. Routledge, London. <https://doi.org/10.4324/9781315261737>
- Home | ASCE [WWW Document], (2023). URL <https://www.asce.org/> (accessed 12.4.23).
- Hudson, P.T.W., Stephens, D. (2000). Cost and Benefit in HSE: A Model for Calculation of Cost-Benefit using Incident Potential, in: *SPE International Conference and Exhibition on Health, Safety, Environment, and Sustainability*. <https://doi.org/10.2118/61050-MS>
- Hussain, M., Alamri, A., Zhang, T., Jamil, I. (2024). Application of Artificial Intelligence in the Oil and Gas Industry, in: Chakir, A., Andry, J.F., Ullah, A., Bansal, R., Ghazouani, M. (Eds.), *Engineering Applications of Artificial Intelligence*. Springer Nature Switzerland, Cham, pp. 341–373. https://doi.org/10.1007/978-3-031-50300-9_19
- IADC.org [WWW Document], n.d. IADC.org. URL <https://iadc.org/> (accessed 6.6.25).
- ILO Statistics and databases [WWW Document] (2023). URL <https://www.ilo.org/global/statistics-and-databases/lang--en/index.htm> (accessed 12.4.23).
- IOPG data [WWW Document], n.d. URL <https://data.iogp.org/> (accessed 7.20.24).
- Isa, A.A.M., Wahab, W.A., Omar, R.C., Nordin, M.Z.M., Taha, H., Roslan, R. (2021). Factors influencing the compliance of workplace safety culture in the government-linked company (GLC). *E3S Web Conf.* 325, 06005. <https://doi.org/10.1051/e3sconf/202132506005>
- Izaye, C.A. (2024). Safety, Health, and Its Relation to Reliability in the Oil and Gas Industry. *Int. J. Pet. Gas Eng. Res.* 7, 7–16.
- Jääskeläinen, A., Tappura, S., Pirhonen, J. (2022). The path toward successful safety performance measurement. *J. Safety Res.* 83, 181–194. <https://doi.org/10.1016/j.jsr.2022.08.014>
- Javay, A., Zaini, M.Z., Almana, A., Yurtaev, V. (2024). Improving Rig Floor Safety by Leveraging Artificial Intelligence Capabilities. <https://doi.org/10.2523/IPTC-23482-EA>
- Jusoh, N., Ali, M.W., Abdullah, T.A.T., Husain, A. (2020). The permit to work in relation to an occupational accident at the Petrochemical Plant. *IOP Conf. Ser. Mater. Sci. Eng.* 778, 012127. <https://doi.org/10.1088/1757-899X/778/1/012127>
- Kalidass, S.K., Ravi, J., Mohan, P.K., Senthil, G., Govindarajulu, C. (2023). Evaluation of fire risk assessment in Chennai construction sites using artificial intelligence and BIM: An agenda for the future, in: *AIP Conference Proceedings*. AIP Publishing. <https://pubs.aip.org/aip/acp/article-abstract/2790/1/020018/2908044> (accessed 11.28.24).
- Ketola, J.-M., Liuhamo, M., Mattila, M., (2002). Application of performance-excellence criteria to improvement of occupational safety and health performance. *Hum. Factors Ergon. Manuf. Serv. Ind.* 12, 407–426. <https://doi.org/10.1002/hfm.10024>
- Khan, A., Busafi, M.A., Thuhli, A.A., Siddiqui, S. (2024). Accident and Incident Analysis in the Oil and Gas Sector Using Artificial Intelligence and Machine Learning. *Procedia Comput. Sci.*, 15th International Conference on Emerging Ubiquitous Systems and Pervasive Networks / 14th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare EUSPN/ICTH 2024 251, 295–302. <https://doi.org/10.1016/j.procs.2024.11.113>

- Leveson, N., (2004). A new accident model for engineering safer systems. *Saf. Sci.* 42, 237–270. [https://doi.org/10.1016/S0925-7535\(03\)00047-X](https://doi.org/10.1016/S0925-7535(03)00047-X)
- Leveson, N.G. (2016). *Engineering a Safer World: Systems Thinking Applied to Safety*. The MIT Press.
- Liu, Y., (2022). Artificial Intelligence and Its Application in the Educational Industry. *Front. Educ. Res.* 5. <https://doi.org/10.25236/FER.2022.050608>
- Lortie, M., Pelletier, R. (1996). Incidents in manual handling activities. *Saf. Sci.* 21, 223–237. [https://doi.org/10.1016/0925-7535\(95\)00066-6](https://doi.org/10.1016/0925-7535(95)00066-6)
- Maddox, K.H., Butler, J.D., Bonsall, D.A. (1991). Permit To Work Procedures, in: SPE International Conference and Exhibition on Health, Safety, Environment, and Sustainability. <https://doi.org/10.2118/23239-MS>
- Mannan, S. (2014). Chapter 9 - Human Factors and Human Error, in: Mannan, S. (Ed.), *Lees' Process Safety Essentials*. Butterworth-Heinemann, Oxford, pp. 143–154. <https://doi.org/10.1016/B978-1-85617-776-4.00009-9>
- Marsden, E. (2017). Heinrich's domino model of accident causation [WWW Document]. *Risk Eng.* URL <https://risk-engineering.org/concept/Heinrich-dominos> (accessed 10.3.24).
- Martinez, A.I. (2023). Two dead, output impacted after fire engulfs Mexican oil platform | Reuters [WWW Document]. URL <https://www.reuters.com/world/americas/fire-breaks-out-pemex-offshore-platform-cantarell-complex-source-2023-07-07/> (accessed 6.9.24).
- Mei, X., Ma, W., Xu, F., Zhang, Z., (2024). Vision-Based Detection of Unsafe Worker Guardrail Climbing Based on Posture and Instance Segmentation Data Fusion. *J. Constr. Eng. Manag.* 150, 04024156. <https://doi.org/10.1061/JCEMD4.COENG-14266>
- Mitreă-Curpanaru, G.G.L. (2021). Performance management – a strategic and integrated approach to ensuring the success of organizations. *IOP Conf. Ser. Mater. Sci. Eng.* 1169, 012039. <https://doi.org/10.1088/1757-899X/1169/1/012039>
- Muley, S., Wang, C. (2024). Hidden Iceberg of Construction Safety: Assessing Near-Miss Recognition Performance under Stress through a Personality Lens, in: Leathem, T., Collins, W., Perrenoud, A. (Eds.), *Proceedings of 60th Annual Associated Schools of Construction International Conference, EPiC Series in Built Environment*. Easy Chair, pp. 876–884. <https://doi.org/10.29007/qbzc>
- Naji, G.M.A., Isha, A.S.N., Alazzani, A., Saleem, M.S., Alzoraiki, M. (2022). Assessing the Mediating Role of Safety Communication Between Safety Culture and Employees' Safety Performance. *Front. Public Health* 10. <https://doi.org/10.3389/fpubh.2022.840281>
- Neal, A., Griffin, M.A. (2006). A study of the lagged relationships among safety climate, safety motivation, safety behavior, and accidents at the individual and group levels. *J. Appl. Psychol.* 91, 946. <https://psycnet.apa.org/doi/10.1037/0021-9010.91.4.946>
- Nowobilski, T., Hoła, B. (2023). Methodology based on causes of accidents for forecasting the effects of falls from scaffoldings using the construction industry in Poland as an example. *Saf. Sci.* 157, 105945. <https://doi.org/10.1016/j.ssci.2022.105945>
- Nunnally, J.C. (1978). An Overview of Psychological Measurement, in: Wolman, B.B. (Ed.), *Clinical Diagnosis of Mental Disorders: A Handbook*. Springer US, Boston, MA, pp. 97–146. https://doi.org/10.1007/978-1-4684-2490-4_4
- Ochulor, O.J., Sofoluwe, O.O., Ukato, A., Jambol, D.D., Ochulor, O.J., Sofoluwe, O.O., Ukato, A., Jambol, D.D. (2024). Technological advancements in drilling: A comparative analysis of onshore and offshore applications. *World J. Adv. Res. Rev.* 22, 602–611. <https://doi.org/10.30574/wjarr.2024.22.2.1333>
- Oil and Gas Well Drilling and Servicing - Site Preparation [WWW Document], 2018. URL <https://www.osha.gov/etools/oil-and-gas/site-preparation> (accessed 6.8.24).
- OnePetro [WWW Document], n.d.. OnePetro. URL <https://onepetro.org/> (accessed 6.6.25).
- Open Access journals and books | ScienceDirect.com [WWW Document], n.d. URL <https://www.sciencedirect.com/browse/journals-and-books?accessType=openAccess> (accessed 12.4.23).
- Othman, N., Nazirmdzabit, M., & Othman, N. (2022). Solid State Technology Validation Measurement, Factor Analysis, and Reliability of Mathematics Teaching Practice Instruments Among Secondary School Mathematics Teachers. *Solid State Technol.* Volume: 63. <https://doi.org/10.53022/oarjet.2024.6.1.0012>
- Ozguc, O. (2021). The assessment of impact damage caused by dropped objects on floating offshore structures. *Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ.* 235, 491–510. <https://doi.org/10.1177/1475090220972586>

- Patidar, A.K., Agarwal, U., Das, U., Choudhury, T., 2023. Understanding the Oil and Gas Sector and Its Processes: Upstream, Downstream, in: Understanding Data Analytics and Predictive Modelling in the Oil and Gas Industry. CRC Press.
- Peatie, J.S., Haroglu, H., Umar, T. (2024). Barriers to achieving satisfactory dropped objects safety performance in the UK construction sector. *Heliyon* 10. <https://doi.org/10.1016/j.heliyon.2024.e37413>
- Perkinson, L. (2018). Incident Investigation: A Culture Change Tool?, in: SPE International Conference and Exhibition on Health, Safety, Environment, and Sustainability. <https://doi.org/10.2118/190542-MS>
- Pillay, M. (2015). Accident Causation, Prevention and Safety Management: A Review of the State-of-the-art. *Procedia Manuf.*, 6th International Conference on Applied Human Factors and Ergonomics (AHFE 2015) and the Affiliated Conferences, AHFE 2015 3, 1838–1845. <https://doi.org/10.1016/j.promfg.2015.07.224>
- Podgórski, Daniel (2015). Measuring operational performance of OSH management system – A demonstration of AHP-based selection of leading key performance indicators. *Saf. Sci.* 73, 146–166. <https://doi.org/10.1016/j.ssci.2014.11.018>.
- Polit, D.F., Beck, C.T. (2004). *Nursing Research: Principles and Methods*. Lippincott Williams & Wilkins. <https://DOI.org/10.1007/978-1-4614-3360-6>
- Ponomarenko, T., Marin, E., Galevskiy, S. (2022). *Energies* | Free Full-Text | Economic Evaluation of Oil and Gas Projects: Justification of Engineering Solutions in the Implementation of Field Development Projects. *MDPI* 15, 3103. <https://doi.org/10.3390/en15093103>
- Praino, G. & Sharit, J. (2016). Written work procedures: Identifying and understanding their risks and a proposed framework for modeling procedure risk. *Saf. Sci.* 82, 382–392. <https://doi.org/10.1016/j.ssci.2015.10.002>
- Purwoko, H., Kamsariaty, Rubadi, Saksana, J.C., Soehaditama, J.P. (2023). Key Performance Indicator: Concept, Implementation to Performance Management. *East Asian J. Multidiscip. Res.* 2, 3261–3268. <https://doi.org/10.55927/eajmr.v2i8.5282>
- Rabenu, E. (2021). *Twenty-First Century Workplace Challenges: Perspectives and Implications for Relationships in New Era Organizations*. Bloomsbury Publishing PLC.
- Radhakrishna, S. (2015). Culture of blame in the National Health Service: consequences and solutions. *Elsevier BV*. <https://doi.org/10.1093/bja/aev152>
- Reason, J. (1990). The contribution of latent human failures to the breakdown of complex systems. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 327, 475–484. <https://doi.org/10.1098/rstb.1990.0090>
- Robinson, C.G. (1983). Pareto analysis: diagnosing investments in managerial ego. *South Afr. J. Bus. Manag.* 14, 109–112.
- Rongrong, S., Xin, S., Qing, L., Baifeng, N., Bing, Z. (2020). Application of Intelligent Safety Supervision Based on Artificial Intelligence Technology, in: 2020 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS). Presented at the 2020 IEEE Conference on Telecommunications, Optics and Computer Science (TOCS), pp. 429–431. <https://doi.org/10.1109/TOCS50858.2020.9339756>
- Rouse, W.B., Cody, W.R., Boff, K.R. (1991). The human factors of system design: Understanding and enhancing the role of human factors engineering. *Wiley* 1, 87–104. <https://doi.org/10.1002/hfm.4530010108>
- Saed, M.B. & Omar, A.F.B. (2024). Applying Safety Lessons Learned from Commercial Aviation to the Oil and Gas Industry. *Int. Sci. Technol. J.* 34.
- Safety performance indicators – 2018 data, 2019. IOGP Publ. Libr. URL <https://www.iogp.org/bookstore/product/safety-performance-indicators-2018-data-fatal-incident-reports/> (accessed 6.9.24).
- Safety performance indicators - 2022 data, 2023. IOGP Publ. Libr. URL <https://www.iogp.org/bookstore/product/safety-performance-indicators-2022-data/> (accessed 6.9.24).
- Sample Size in Statistics [WWW Document], 2017. Stat. To. URL <https://www.statisticshowto.com/probability-and-statistics/find-sample-size/> (accessed 7.23.24).
- Semyonov-Tal, K., Lewin-Epstein, N. (2021). The importance of combining open-ended and closed-ended questions when conducting patient satisfaction surveys in hospitals. *Health Policy OPEN* 2, 100033. <https://doi.org/10.1016/j.hopen.2021.100033>
- Shapiro, M.J. (2003). High reliability organizational change for hospitals: translating tenets for medical professionals. *BMJ*. <https://doi.org/10.1136/qhc.12.4.238>

- Sigall, H. & Mills, J. (1998). Measures of Independent Variables and Mediators Are Useful in Social Psychology Experiments: But Are They Necessary? *Personal. Soc. Psychol. Rev.* 2, 218–226. https://doi.org/10.1207/s15327957pspr0203_5
- Solanki, P., Baldaniya, D., Jogani, D., Chaudhary, B., Shah, M., Kshirsagar, A. (2022). Artificial intelligence: New age of transformation in petroleum upstream. *Pet. Res.* 7, 106–114. <https://doi.org/10.1016/j.ptlrs.2021.07.002>
- Šolc, M., Blaško, P., Girmanová, L., Kliment, J. (2022). The Development Trend of the Occupational Health and Safety in the Context of ISO 45001:2018. *Standards* 2, 294–305. <https://doi.org/10.3390/standards2030021>
- Stewart, J.M. (2001). The turnaround in safety at the Kenora pulp & paper mill. *Prof. Saf.* 46, 34.
- Stewart, L., (2024). Variables in Research | Types, Definition & Examples [WWW Document]. ATLAS.ti. URL <https://atlasti.com/research-hub/types-of-variables-in-research> (accessed 10.27.24).
- Sujan Kumar, M., Deivanathan, R. (2021). Effect of process parameters on drilling — An overview. *Mater. Today Proc.*, 28th International Conference on Processing and Fabrication of Advanced Materials (PFAM28) 46, 1401–1406. <https://doi.org/10.1016/j.matpr.2021.02.574>
- Taillant, J.D. (2018). Fracking Well Blows in Argentina Spewing Gases and other Toxic Chemicals into the Environment – Center for Human Rights and Environment. URL <https://center-hre.org/fracking-well-blows-in-argentina-spewing-gases-and-other-toxic-chemicals/> (accessed 6.8.24).
- Talukdar, S. (2021). Report on Baghjan blowout says it may take more than 10 years for even a partial recovery of the destruction caused to the landscape [WWW Document]. Frontline. URL <https://frontline.thehindu.com/environment/disaster-baghjan-oil-well-blowout-tinsukia-assam-2021-report/article34987694.ece> (accessed 6.9.24).
- Tremblay, A. & Badri, A. (2018). Assessment of occupational health and safety performance evaluation tools: State of the art and challenges for small and medium-sized enterprises. *Saf. Sci.* 101, 260–267. <https://doi.org/10.1016/j.ssci.2017.09.016>.
- UK HSE Executive Health and Safety Statistics - HSE [WWW Document], 2023. URL https://www.hse.gov.uk/statistics/?utm_source=hse.gov.uk&utm_medium=referral&utm_campaign=annual-stats-23&utm_term=annual-stats-banner&utm_content=home-page-banner (accessed 12.4.23).
- Wagenaar, W.A., Hudson, P., Reason, J. (1990). Cognitive failures and accidents. *Wiley* 4, 273–294. <https://doi.org/10.1002/acp.2350040405>
- Walhekar, A. & Khatke, A. (2020). A Study of Performance Management System as a Strategic Tool of HRM. *Int. J. Res. Eng. Sci. Manag.* 3, 155–157. <https://doi.org/10.47607/ijresm.2020.358>
- Wertz, J. (2018). Authorities Investigating Oklahoma Rig Explosion, Deadliest U.S. Drilling Accident In Years | StateImpact Oklahoma. StateImpact Okla. *Environ. Educ. Energy Health Justice Policy People*. URL <https://stateimpact.npr.org/oklahoma/2018/01/25/authorities-investigating-oklahoma-rig-explosion-deadliest-u-s-drilling-accident-in-years/> (accessed 6.9.24).
- Wood, D.A. (2024). Chapter 6 - Real-time monitoring and optimization of drilling performance using artificial intelligence techniques: a review, in: Wood, D.A., Cai, J. (Eds.), *Sustainable Natural Gas Drilling, The Fundamentals and Sustainable Advances in Natural Gas Science and Eng.* Elsevier, pp. 169–210. <https://doi.org/10.1016/B978-0-443-13422-7.00017-9>.
- Xian, L.W., Takaijudin, H. Binti, Othman, I. bin (2022). Safety Leading Indicators for the Malaysian Construction Industry. *J. Posit. Sch. Psychol.* 7862–7876. <https://www.journalppw.com/index.php/jpsp/article/view/8864> (accessed 12.7.24).
- Zahed, M.J. (2024). Human Perception of Collision and Safety in Autonomous Flight Scenarios (Master of Science). PennState <https://etda.libraries.psu.edu/catalog/34377mpz5259> (accessed 12.3.24).