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Health, Safety, and Environmental (HSE) Predictive Analytics for Offshore Operations

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Abstract
Health, Safety, and Environment (HSE) predictive analytics embraces new functionalities and advances the field of offshore analytics. This integration advances analytics offshore, where the external environment and industry risk come together. The role of HSE analytics offshore has been reactive in nature and predictive for incident analytics. This coming together of HSE analytics with real-time data streams and predictive analytics to forecast incidents that can occur is the current status of HSE analytics offshore. The use of real-time data streams with predictive analytics eases the pace at which reactive analytics are done, while providing the outcomes in real-time, allowing for forecasted incidents to be prepared for. The focus of analytics offshore is primarily analytics and integrating with the data streams, which dives into offshore environment monitoring systems. The input in risk models forecasted real-time data into the analytics. The real-time data provides inputs on infrastructural failures, machinery, and operational conditions. An instance of predictive analytics can be used in systems where abnormal vibrations occur that can lead to blowouts. These predictive models lessen the time from analytics to operationalization. Hence, enabling real-time decision support systems, these systems aid in shifts and compliance with emergency preparedness and international safety standards.
The more general implication of predictive analytics is its role in enhancing the efficiency and sustainability of offshore operations. By reducing the expenses of unplanned downtime and expensive accidents, predictive safety frameworks economize operational costs and also strengthen environmental protection through early containment of pollution incidents. in addition, these frameworks help meet the legally-bound and self-imposed zero-harm goals, and also the DOE and DHS resilience goals offshore of critical infrastructure. Predictive safety analytics frameworks are crucial in maintaining the safety and protection of people and the marine environment, and equally critical in maintaining the robust, operational stability of offshore industries in the face of unpredictable risks.

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1. Introduction

The management of Health, Safety, and Environment (HSE) has always been fundamental to the operations of offshore oil, gas, and renewable energy (Simpson *et al*., 2019; OJO and AYO, 2021). Offshore areas are difficult and dangerous because of seclusion, high pressure, complicated machines, and unpredictable ocean conditions. These elements increase the risk of equipment breakdown, structure failure, blowouts, fires, and spills, which puts workers, machines, and the environment in danger (Akashraj and Maleith, 2020; Brkić, D., and Praks, 2021). Furthermore, the offshore industry is subject to public and legal oversight due to the potential for catastrophic environmental damage (Giannopoulos, 2019; Roos, 2019). The reputation of the industry is on the line, as it provides a large amount of the energy used in the world. Because that reputation is on the line, there is a need for trust in the industry, as well as a need to fulfill operational, legal, and ecological duties (Mantini *et al*., 2019; Gann *et al*., 2019). The maintenance of that trust comes from firm HSE procedures, which prevent damage to nature and humanity.

The focus of traditional HSE management has often been reactive in nature. Safety management systems, in most cases, deal with incidents after they have occurred, determine causes, and take steps to prevent incidents of a similar nature in the future (Niu *et al*, 2019; Arnal-Velasco and Barach, 2021). As a stand-alone approach, there are significant limitations to such approaches. Here, the focus seems to be on learning after an incident, rather than preventing the incident from occurring in the first place. This slow response is what leads near offshore operators to experience downtime, loss of expensive assets, and environmental catastrophes (Atia *et al*, 2019; Nezamian and Kartsounis, 2019). Insurance often relies on near-miss reporting and inspection campaigns, but most of the time, the inefficiencies created from the loss of oil and gas assets and processes outweigh the near-miss traces and human errors instead (Chenoweth *et al*, 2019; Zhou *et al*, 2019). As we deal with increasingly complex offshore infrastructure, reactive approaches are no longer sufficient to ensure the resilience and sustain the critical energy systems (Cantelmi *et al*. 2021; Council 2021).

To understand and alleviate these pain points, predictive analytics is being regarded as a game-changer in HSE management on offshore activities. Predictive Analytics is the use of statistics, machine learning, and modeling to find and understand patterns in large and complex data sets (Kelleher *et al*. 2020; Sarker, 2020) in so-called 'hidden data'. Predictive analytics enables stakeholders to discern patterns and trends in data, unlike its predecessors, which provide the means to ascertain and take action on latent and immediate risks. By combining training records, inspection data, and historical accident records, predictive analytics can reveal the remarkable correlations between human skills, equipment status, and environmental factors (Sarkar *et al*. 2019; Ajayi *et al*. 2019). This broad-sighted perspective revitalizes safety management by shifting the approach from a mere compliance-based approach to a fluid and agile approach driven by data. For instance, a predictive model can signal a lack of refresher training, coupled with added maintenance, as a heightened risk for operational accidents during surge storm conditions. Signals like these enable proactive operators to implement operational safety measures, which in turn lead to lower risks to workers and the surrounding environment (Raja and Iqbal 2020; Thomas and Brown 2020).

On predictive tools, Bayesian networks are one of the most promising tools for offshore HSE work. This is because these models capture cause-and-effect relationships among diverse risk factors, and they can also update predictions in real-time as new data comes in. This means that in practice, the odds of an accident can be constantly recalibrated and adjusted based on new inspection data, changing environmental factors, or workforce productivity metrics. In addition, Bayesian models can also be used for scenario testing, which is when operators simulate how certain actions, like more advanced training or more frequent inspections, would decrease the chances of an accident. The combination of uncertainty and actionable decision support is what makes predictive analytics optimally suited for the unpredictable and high-stakes context of offshore work (Marcus *et al*., 2020; Enemosah in 2021).

The goal of predictive HSE analytics exercises is to minimize risk through the integration of data of varied origins into predictive frameworks. These data sets establish the risk profile when joined to a predictive model. Training records are helpful about human reliability; inspection data are helpful regarding technical integrity; and accident records expose systemic flaws. These data sets are multi-function to enhance proactive management techniques to help achieve operational and environmental efficiencies. Providing offshore operators with the ability to optimize resource allocation and demonstrate leadership in responsible energy production, predictive models in risk management provide an operational shift towards proactive safety management (Kosmowski and Gołębiewski, 2019; Yakoot *et al*., 2021).

The use of analytics in predictive models for offshore HSE management is as much a cultural shift as it is a technological change. It is a change, for example, from establishing timelines retroactively to establishing them proactively; from risk silos to risk models; from having safety as a regulatory requirement to having safety as a regulatory goal. As offshore energy production pushes into deeper waters and more intricate settings, predictive analytics will be key to safeguarding lives, delicate ecosystems, and vital energy infrastructure (Levin *et al*., 2019; Jahanbakht *et al*., 2021).

2. Methodology

An extensive evaluation of health, safety, and environmental (HSE) predictive analytics in offshore operations was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. The selection, screening, eligibility evaluation, and inclusion of pertinent studies from peer-reviewed journals, conference proceedings, industry reports, and regulatory publications were all guided by a systematic approach. Predefined keywords and Boolean combinations connecting "offshore operations," "predictive analytics," "machine learning," "health and safety," and "environmental monitoring" were used to conduct a systematic search of electronic databases, including Scopus, Web of Science, PubMed, IEEE Xplore, and ScienceDirect. To lessen publication bias and capture new industry practices, grey literature was integrated by examining technical standards, international recommendations on offshore safety and environmental risk management, and organizational white papers.

After importing the studies from the first search into a reference management program, duplicates were eliminated, and then irrelevant information was filtered out by title and abstract. Research directly addressing predictive modeling, risk forecasting, safety performance assessment, or environmental hazard prediction in offshore oil, gas, and renewable energy operations was given priority in the eligibility phase, which involved a full-text review of the shortlisted papers against inclusion criteria. Papers lacking methodological rigor, those not concentrating on offshore situations, and studies that only included descriptive analyses devoid of predictive elements were eliminated based on exclusion criteria.

Author information, study goals, offshore operational environment, prediction techniques used, model performance metrics, and reported HSE results were all captured during data extraction using a consistent framework. Using modified appraisal checklists, the included studies' quality was assessed for methodological soundness, repeatability, data integrity, and usefulness to offshore risk management. In order to group findings based on predictive techniques like statistical modeling, machine learning, real-time sensor analytics, and digital twin simulations, as well as their implications for accident prevention, safety training optimization, and environmental incident minimization, the synthesis process comprised a narrative and thematic analysis. This guaranteed reproducibility and made it possible to critically assess the scope and constraints of the evaluated literature. The methodology provided a rigorous foundation for evaluating how predictive analytics is being operationalized to enhance offshore HSE performance, strengthen risk-informed decision-making, and support the transition toward more proactive, data-driven safety and environmental management systems.

2.1. Data Foundations for HSE Predictive Analytics

In elastic forecasting, both the quality and heterogeneity of the data are of key importance. While offshore oil, gas, and renewable energy activities yield irrefutable volumes of data, extracting useful risk assessments from untamed data still needs to be formulated within a schematic infrastructure (Nguyen *et al*. 2020; Adebisi *et al*. 2021). Predictive models are built on the amalgamation of training records, inspection diaries, accident and near-miss archives, and environmental monitoring data, as shown in Figure 1. They capture offshore risk in its multifaceted human, technical, and environmental, in a manner that permits the use of predictive tools like Bayesian networks to determine associations, estimate the risk of an accident, and prescribe accident preventive measures.

Reliability is a principal concern when assessing offshore safety performance, and training records offer an objective dimension upon which the effectiveness of a workforce at any moment in time could be determined. Competency assessment is typically extensive in composition, covering both the operational (equipment handling, confined space entry, etc.) and the emergency response (firefighting, evacuation, first aid, etc.) spectrums. Predictive models are able to capture not only individual determinants of readiness, but also the systemic workforce vulnerabilities through the digitization and standardization of the assessments (Scholz *et al*. 2020; Trenerry *et al* 2021).

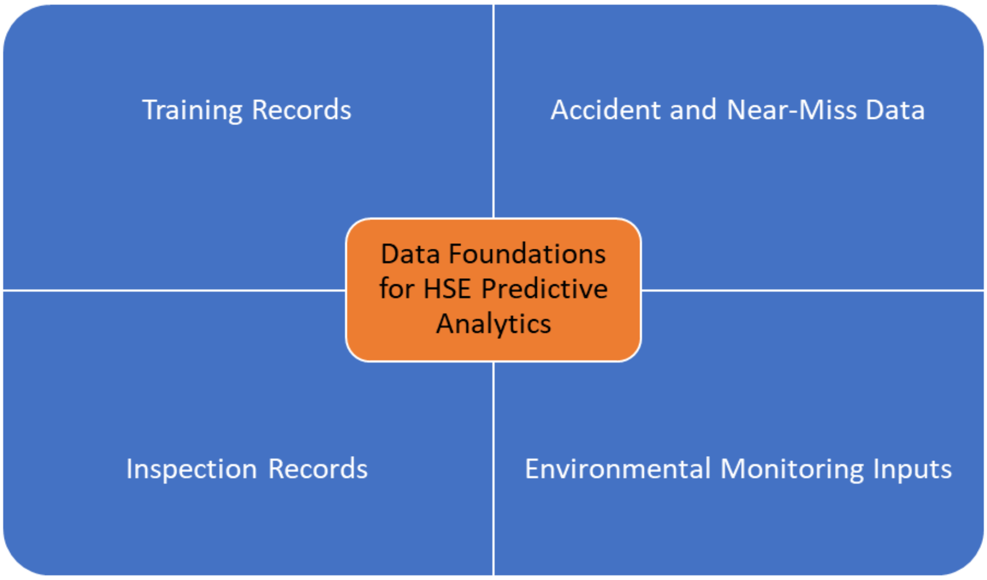

Fig 1: Data Foundations for HSE Predictive Analytics

Analyzing the frequency and quality of safety drills, certifications, and refresher courses is also significant. Practical skills are easily lost on the job, especially in offshore environments. For example, personnel not engaged in recurrent evacuation exercises would likely respond poorly to emergencies and exacerbate accident situations. The collection and analysis of training data, as well as recertification schedules, simulation drills, and performance results, provide the ability to reveal trends in safety unpreparedness.

In predictive analysis, it becomes possible to measure a gap between training and retraining effectiveness and incident occurrence rates. Linking these separate datasets to historical accident and near-miss archives allows us to evaluate whether certain enhanced trainings can decrease the accident threshold, or whether other specific skills are lacking. This approach allows operators to ensure that the resources are allocated effectively, particularly in relation to enhanced training opportunities, in order to eliminate the human error factor, which is often a significant contributor to offshore incidents (Williams *et al*. 2019, Chandrasegaran *et al*. 2020). From the perspective of offshore HSE incidents, technical breaks are still their most important cause. Maintenance logbooks are central to the prognosis of equipment condition, for which key parameters are the monitoring of subsea pipelines for corrosion, risers and support beams for structural component fatigue, and drilling system pressure vessels for integrity (Amaechi *et al*., 2019; Hameed *et al*., 2021). These monitoring data form the basis for equipment reliability forecasting and high-risk asset identification.

Condition monitoring is enhanced by non-destructive testing (NDT) data that improves operational insights by offering structural reliability assessments that do not interfere with equipment functionality (Grace and John 2019; OGUNNOWO *et al*. 2020). Without a system's collapse, predictive models can be augmented by NDT-derived parameters for estimating system component degradation to determine system component replacement.

The scheduled maintenance and emergency repairs logs are handy for recording maintenance procedures. These documents help clarify inspection outcomes and allow forecasting analytics to assess whether maintenance activities were successful. For instance, subsystems that need excessive repairs over time may suffer from design problems or maintenance procedures that are unstated. Combining inspection and maintenance records allows computer models to generate degradation trajectories. In turn, the computer models could indicate potential breakdowns that could improve operational productivity and mitigate HSE risks through advanced strategies (Merkt, 2019; Aivaliotis *et al*., 2021).

The history of accidents and near misses is equally important for training predictive HSE models. In HSE modules, incident records are broken down according to the impact level, the reason, and the systems involved. This breakdown serves as the base for estimating risks. These datasets help probability models in recognizing failure patterns, such as the relations between weather conditions and lifting accidents or poor training and overuse of tools (Dindar *et al*., 2018; Reder *et al*., 2018).

The use of near-miss reporting systems is valuable in identifying skills needed in an accident reporting system since they do contain consequences. The metric on near misses highlights operational weaknesses, which, if unsolved, can lead to major accidents. Predictive analytics weighs near-miss frequency and near-miss severity to predict arising risks, which is beneficial for operators as they can take preventive steps to mitigate harm (Du *et al*., 2020; Renga *et al*., 2020). It should be noted, however, that the system is only as strong as the willingness of the operatives to report the system without fear of sanction; thus, a strong safety culture is needed.

The rest of the branches of root cause analysis also provide value by enriching datasets on accidents and near misses by connecting incidents to system and human underlying operational reasons and factors. A root cause analysis might, for instance, determine that equipment failure is more than a technical error; along the same line, there are also insufficient inspection intervals and an absence of sufficient operator training. Using these records in forecasting systems improves causal analysis and, in particular, helps Bayesian networks to more realistically capture the interdependencies of human, technical, and external system elements.

HSE analytics greatly benefit from having oceanographic and meteorological datasets—like current and wind speed and temperature changes—monitored and stored (Skliris *et al*., 2021; Jimenez-Martinez, 2021). For instance, strong currents elevate the chances of dropping some tools and equipment, and in extreme temperatures, the personnel cannot concentrate and make decisions.

Environmental Impact Assessments (EIA) add baseline protective models relating to historical spills, emissions, and more to highlight areas needing environmental protection and baseline data for estimating the impact of future spills. Predictive models assess likely consequences and measure severity, but, in isolation, they are not enough to manage environmental risk deeply. By combining EIAs and accident statistics, integrated risk management is achieved, allowing analytics to focus on sustainability as much as on safety (Yang, 2019; Hagenlocher *et al*., 2020).

Broader considerations regarding the integration of HSE performance indicators with other sustainability goals are becoming more relevant due to the global transitions in climate and energy. Models for forecasting compliance with international legal obligations, including greenhouse gas emissions, spill and waste management, and other spill management predictive modeling, yield more than compliance with corporate international legal obligations. It also furthers corporate social responsibility (Jagoda and Wojcik, 2019; Döring *et al*, 2020). The role of analytics integration is integrative predictive analytics for proactive accident prevention. It, for the first time, incorporates other environmental custodianship to engrain long-term stewardship thinking.

How far and how quickly predictive HSE analytics work in offshore settings hinges on analytics data foundations. Training and competence records, together with inspection and maintenance records, capture technical/maintenance reliability, accidents and near misses, and operational vulnerabilities, while environmental monitoring defines dynamic natural systems and their operational risks. When combined, these data sets form predictive models for forecasting accidents, aiding intervention selection, and alignment with offshore operations goals on sustainability and safety. This is how the offshore industry, based on these foundations, can move away toward proactive risk prevention and away from managing incidents, within an increasingly complex and challenging operational context (Mentes and Turan, 2019; Pedersen and Ahsan, 2020).

2.2. Predictive HSE Risk Model

The health, safety, and environmental (HSE) management for operations in offshore oil, gas, and renewables is moving into an emerging phase and is characterized by the proactive, data-infused strategies for accident prevention. Reactive strategies—those that attend to incidents after the fact—have consistently proven inadequate for minimizing risks in the contracting, and ever more complex, offshore domains. A predictive HSE risk model aims to forecast accident probability and thus guide the stakeholders in purposeful risk management, enabling them to take proactive steps to address the risks before they spiral into large-scale incidents (KODOTH and SHIBUTANI, 2019; Mahesh, 2020). Such models integrate disparate sets of data and employ sophisticated analytics to address offshore risks and are invaluable to enhance operational safety, attend to environmental protection, and improve efficiency in the deployment of HSE resources.

The predictive HSE risk model is designed to demonstrate potential actionable foresight into prospective accidents and environmental damages. The model is not intended to serve any chronology of incidents, and thus allow them to serve as a relic of risk reporting, as doing so would disarm their purpose in forecasting. The more these models are used, the greater their operational contexts are, which means that they diversify the avenues through which quantifiable accidents are predicted, as shown in Figure 2. Assumption-driven estimates enable operators to address prospective high-risk scenarios in preventive maintenance, training, and safety resource allocation. Furthermore, aligned with their complex reporting requirements, the model arms the de facto regulators and policymakers with calculated evidence of compliance, enabling them to pursue the dynamic compliance and resilience primary to new national and international safety regimes (Eyinade *et al*., 2021; Behnassi *et al*., 2021).

1. Input Layer

In essence, this is where the data is presented to the predictive risk model. The training records detail insights into the workforce competency and the cycles of certification. They also provide the results of the safety drills and the human dimension of risk (Fabianoa *et al*., 2019; Raza *et al*., 2019). The technical system integrity is captured by Non-Destructive Testing (NDT) results and Inspection and maintenance records. The datasets on accidents and near-accidents depict historical vulnerabilities and give proof of operational risk. The combination of these records, which pertain to the offshore operations, is diverse enough to respond to the system of human, technical, and systemic risks.

2. Processing Layer

In this, the framework utilizes the predictive risk model to derive the structures from the datasets that are raw. These structures are the ones to which predictive modeling is applied. To establish some baseline tendencies and to find records of some patterns and anomalies, statistical analysis is central to this. To improve the records of data, the processes of denoising, imputing, missing value, and accentuating risk features (Obaid *et al*., 2019; Bernard *et al*., 2019) are applied to the data. These processes are known as machine learning pre-processing methods. This stage also ensures that the data that is retrieved from the model is consistent and that there are no gaps in reporting, which can undermine the predictive accuracy of the model. It also ensures that the system is able to capture relationships that are multidimensional and complex within the datasets.

3. Predictive Layer

The most central component of any model is its predictive layer. In this case, a Bayesian network is used to model the likelihood of an accident occurring. Bayesian networks are considered offshore HSE applications because they depict the conditional dependency of very different variables. Consider the case of the relationship between poor training, inadequate maintenance, and eventually, equipment failure. They deal with both quantitative (e.g., NDT thickness, number of incidents within a given period) and qualitative information provided by experts within a probabilistic framework (Qing etal, 2019; Kumar etal, 2019). The output is a dynamic risk assessment offshore, which changes as new information is acquired.

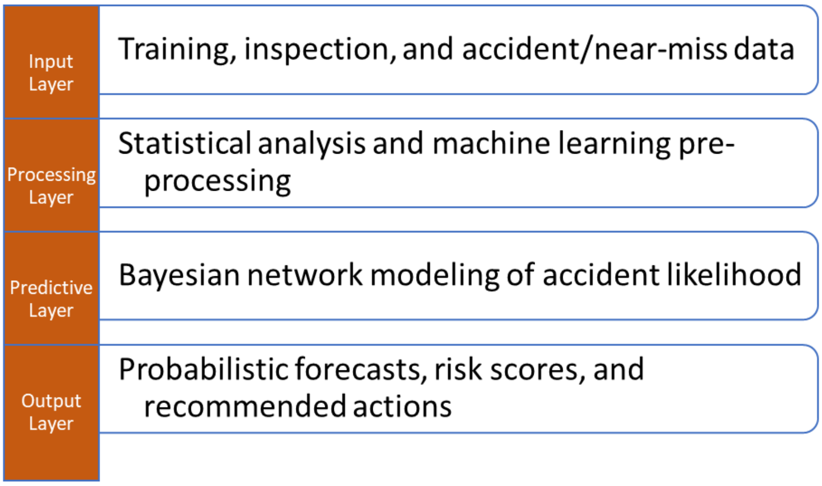

Fig 2: Core Components of Predictive HSE Risk Model

4. Output Layer

At this point, the model is capable of transforming probabilistic estimates into prescriptive aids. The model provides a forecast of the likelihood of an accident occurring, the risk score for key assets, and risk management recommendations for the most influential risk drivers. In a case where the logger forecast predicts a high likelihood of equipment failure because of corrosion, the model prescribed 'maintenance' as the most appropriate action. In a situation where the model predicts a high likelihood of equipment failure and poor training, the model prescribes training as the appropriate response. The use of dashboards, GIS, and mobile applications makes the information available to decision makers, regulatory authorities, and managers (Farmanbar and Rong 2020; Shirowzhan *et al* 2021).

2.2.1. Steps for Model Development.

The first activity that comes to mind for model development is the Physical Planning of the technologies needed. For the training documents, scrubbing includes the removal of certain inconsistencies, outliers, and records that are incomplete records for the logs, inspection reports, and incident databases, as shown in Figure 3. In normalization, processes to ensure that the outliers identified and removed are sufficiently comparable are employed (Ossai, 2019; Nelson *et al*., 2021). For feature selection, predictive attributes such as recertification intervals, corrosion rates, and the intervals between failures of electro-deposition are selected to ensure the model concentrates on the components that have the strongest association with the risk of predictive analytics.

Not all attributes have the same level of power on the likelihood of an accident occurring. The allocation of weights to risk and their historical impact is used to define an influence in proportional increments, Variable weighing (Schlögl, 2020; Norris and Moore, 2020). In methods like these, inspection records with severe fatigue equipment inspection findings are likely to receive more weight than weaknesses in instructional performance and deviation from training guidelines. There is a considerable amount of direct influence on the model based on the real world when using Bayesian methods. Probabilistic weighting and Bayesian

methods, specifically, account for the weight of historical records based on the periodicity and severity of an accident.
The calibration process matches model outcomes to the corresponding real-world results. Cross-referenced historical accident datasets are the benchmarks used to see how estimated probabilities stack up against reality (Moosavi *et al*., 2019; Schlögl *et al*., 2019). Consider the case when a model indicates a 40% chance of equipment failure under certain conditions. Calibration ensures that each of the probabilities the model forecasts actually corresponds with how often that failure happened in the available historical data. This process tightens the parameter values in the Bayesian network to increase accuracy and reduce predictive bias. Calibration evaluates model performance with a sensitivity test by incorporating bias to check that the model behaves in a rational fashion to certain changes in the values of the independent variables.

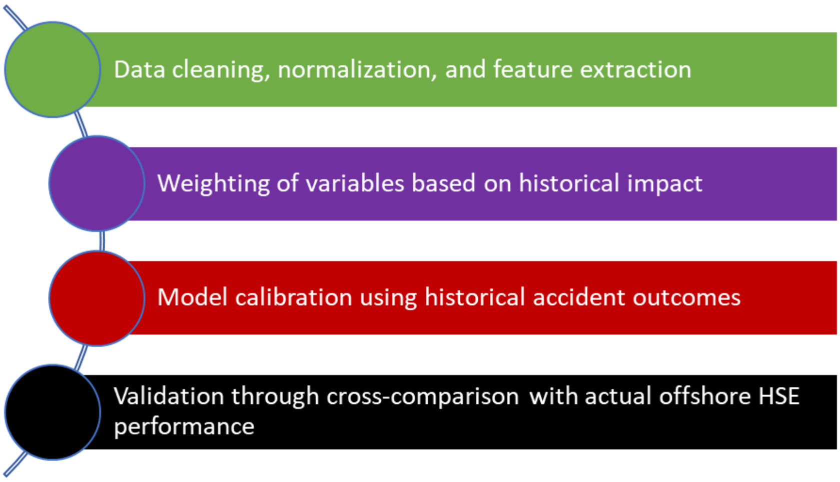

Fig 3: Model Development Steps

Validation serves to foster confidence in the predictive model as a crucial step needed to reinforce certainty in the. Comparative analysis between forecasts and actual historical HSE performance offshore the area of concern on the prediction horizon serves this purpose. Evaluation techniques such as cross-validation and confusion matrix focus on measuring the model's predictive accuracy, precision, and recall. Inconsistency in a validated model should predict constructions and observe accident rates while maintaining different context operational robustness. new diverse model and conditions offshore as real-time data updates, eliminating the inflexibility Wu *et al*, 2021. Zhu and Liyanage 2021.
The predictive HSE risk model is transformative in its approach to assimilating safety and environmental management in regard to offshore operations. By utilizing various inputs, including files pertaining to training and inspection operations, and records of accidents, the model grasps the intricacies of risk offshore. Through its multi-layer structure incorporating statistical preprocessing, predictive Bayesian networks, and predicable of actionable outputs, the model delivers the framework in seventeen risk factors for predicting accidents. Accomplishment of frameworks of predictive models supports regulatory bodies, operators, and policymakers in predicting risk, streamlining safety and intervention measures, and protecting offshore assets, personnel, and the environment in compliance with the 21st-century safety and resilience standards (Bhattacharya *et al*., 2021; Alabi *et al*., 2021).

2.3. Bayesian Networks in HSE Forecasting

The offshore oil and gas industry has one of the highest risks to the health, safety, and environment (HSE) due to the interaction of the human, technological, and ecological systems. Managing risks through traditional methods tends to be deterministic or retrospective, which do not capture the dynamic offshore systems. The offshore oil and gas industry has seen the proliferation of Bayesian Networks (BNs), which are a strong probabilistic framework for forecasting and managing HSE risks. Their pioneering technique of statistical inference and causation facilitates planning in the absence of HSE frameworks (Hoerl and Snee, 2020; Schölkopf *et al*, 2021).
Using Bayesian Networks (BN) for Health, Safety, and Environment (HSE) forecasting for offshore activities is especially useful due to their unique capability in modeling ambiguity. There are multiple interrelated and interdependent risks in offshore environments, such as fatigue, corrosion, equipment, and weather changes, which simultaneously interact in non-linear fashions. Deterministic models are incapable of representing this variability; however, BNs can flexibly encode probabilities that accommodate the uncertainty. Moreover, Bayesian structures can model Archimedean cause-and-effect relations. In such a situation, inadequate training increases the chances of making procedural mistakes, and such mistakes increase the chances of blowouts or spills. Formalizing such dependencies helps BNs (Bayesian networks) to provide a clear model of how such accidents happen. Most BNs are capable of dynamic updating, and this is an additional benefit. BNs can revise probabilities in real time and forecast weather changes for offshore activities, while continuously updating based on new incoming data from inspections, sensors, and reports.
Incorporating nodes, edges, and conditional probability tables, Bayesian Networks are composed in unique graphical models. In HSE implementations, nodes are visualized as crucial constituent risk factors, particular human-level nodes which include factors like training levels, stress and fatigue, as well as technical factors like equipment, corrosion inspection frequency, and environmental variables like temperature, wave height, and storm frequency. An edge

represents probabilistic dependencies between these factors. An edge, for example, linking "equipment condition" and "likelihood of blowout," represents the degrading condition of equipment and the technical degradation of catastrophic events. In the center of any model lies the Conditional Probability Tables, which capture the essence of outcomes given a particular combination of the conditions surrounding the parent node. The probability of a spill in conjunction with severe weather and poor equipment integrity, for example, could be approximated and expressed as 0.6 in the converse case of the moderate weather condition, which is 0.1, with high equipment reliability and integrity. These CPTs are a result of historical data, expert elicitation, and hybrid systems, which include both (Azar and Dolatabad, 2019; Alkhairy, 2020).

As with any other Bayes Networks (BN) application, their offshore HSE (Health, Safety, and Environmental) forecasting employs Bayesian models to perform prediction on blowouts given that equipment integrity is deteriorating and the proficiency of the operator is insufficient. BN assesses the blowouts by taking into account the probabilistic dependencies of the equipment of the drill and the competence of the operator to estimate the blowout event and probabilistic models. This enables the managers to plan on focusing their resources on inspections on proactive training before the blowout event happens. A similar proactive forecasting is also possible employing BNs for severe weather spill forecasting, where HBNs connect weather information with asset domes to calculate spill probabilities, supporting spill response planning. BNs also simplify other primary tasks, such as estimating human errors related to the highly offshore stressful operations, for example, during the rush response to alarms or to navigation during storms. BNs can calculate that the probabilities operator will make a mistake during high stress, different fatigue, and inadequate training. These forecasts, together with fatigue management and work-rest systems, provide a sound basis for their planning. These examples demonstrate the shift in focus of HBN from checklists to dynamic, multi-dimensional context forecasting.

Other than forecasting, Bayesian Networks can also serve as powerful L tools in the planning phase of interventions. By “running through simulations of what-if scenarios, managers can assess the value of the safety interventions proposed. One network can assess what amount of risk that is decreased due to increased training frequency or increased inspection frequency. Such models assist in assessing the value of the proposed decisions, enabling them to suggest interventions that would improve the overall safety. The uniqueness of this phenomenon is that the Bayesian Network is able to capture critical components of the system that, when intervened upon, would produce a massive decrease in risk (Sheehan *et al*., 2019; Pirbhulal *et al*., 2021). One model could suggest that one of the best ways to decrease the chances of human error is not additional training but instead reducing fatigue. Also, one could suggest that there is more safety to be gained from improving the inspection intervals than there is from enhancing the inspection criteria. This ability to identify the greatest capture of value or high leverage variables ensures that the interventions taken are most likely to produce the greatest overall risk reduction, ensuring safety is retained.

Bayesian networks offer a specific and progressive probabilistic approach for improving HSE forecasting within offshore operations. Their modeling of uncertainty, causality, dynamic and complex systems, as well as relationship updating, is particularly relevant to the offshore industry's continuum of evolving risks. By framing risks as interconnected nodes and assessing their interactions through conditional probabilities, BNs allow for advanced forecasting of blowouts, spills, and errors of omission, as well as risks of human intervention. Their use for forecasting is only a fraction of their utility. BN application for intervention planning is more robust due to the intervention simulations that capture critical impact strategies for risk mitigation. Offshore operations are further exposed to the evolution of environmental risk, regulatory scope, and safety issues. In this regard, Bayesian networks offer promising approaches for assessing socio-economic resiliency, advanced risk to human life and marine ecosystems, and streamlined offshore operation economics.

2.4. Implementation in Offshore Operations

Adopting offshore operations’ predictive approaches to health, safety, and environmental issues, as described in (Hasan *et al*. 2020, Hamedifar and Wilczynski 2021), entails selling predictive HSE risk models and analytics offshore, surrounded by, embedded within, and flowing from systems integration as described and delivered in offshore precision systems. These predictive capabilities, integration surrounded by and embedded within operational workflows, enable the offshore response to predicted events to take place in the safest, most environmentally sustainable manner, as shown in Table 1.

Table 1: Implementation in Offshore Operations

Implementation Area	Key Features	Benefits / Impact
Integration with Existing HSE Management Systems	- Embed predictive safety and risk models into real-time monitoring dashboards. - Link with digital twins of offshore assets for holistic visibility of operations and safety conditions.	- Provides continuous monitoring of hazards and operational risks. - Enables proactive interventions before incidents occur. - Enhances situational awareness across offshore operations.
Decision-Support for Managers	- Risk prioritization tools for maintenance scheduling and workforce training. - Scenario testing for emergency preparedness, evacuation planning, and crisis management.	- Optimizes resource allocation based on risk levels. - Improves readiness and reduces response times during incidents. - Supports data-driven decision-making in safety-critical operations.
Regulatory and Compliance Benefits	- Demonstrates proactive safety management to regulators. - Ensures alignment with international safety frameworks (e.g., ISO 45001, OSHA, IMO).	- Strengthens regulatory compliance and audit readiness. - Enhances reputation and stakeholder confidence. - Facilitates integration with global offshore safety standards.

Strong offshore systems in place enhance and complement existing HSE management frameworks as structural elements of the HSE Predictive Models. Demonstrating the fastest response times from offshore stored and processed refined data serves to build operational offshore precision systems capabilities around predictive models. These systems enhance existing offshore operations' SMS, risk registers, and condition-monitoring predictive capabilities to deliver practical offshore operations value from embedded offshore predictive models.

Integrating predictive models into monitoring dashboards is a particularly promising direction.The dashboards integrate outputs and therefore give operators and managers rapid feedback on growing risks. The operational dashboards are smart enough to offer what-if analyses and collaborations. For example, if corrosion data and training logs correlate with increased accident potential on a pipeline, the system will actively alert trainers when they are scheduled to offer training on that topic.

An equally important development is the integration of predictive models with digital twins of offshore assets. Digital twins are used offshore for condition monitoring and performance enhancement (let's integrate your HSE analytics in these functional models). This integration can extend to scenario-building simulations, changing any combination of competency, equipment, and environment to assess the impact on accidents. This can significantly improve decision confidence.

On the other hand, the analytics must address the integration of predictive models with decision support systems for managers in charge of resource allocation and strategy formulation. Predictive HSE models offer more than scenario testing and prioritization. Risk prioritization tools maximize the efficiency of resource allocations by determining the most important risks associated with offshore assets. For example, risk predictions may identify specific operations lifting associated with subsea valves or emergency drills as disproportionately high risk. Managers can target high-risk areas and allocate maintenance activities, refresher training, or targeted inspections so that the federal budget and personnel are deployed where they can provide the most safety benefit.

Scenario testing is another step that enhances the use of predictive models during emergencies. Offshore operations are extremely dynamic, and even the ability to run "what-if" scenarios is tremendously valuable. For example, models that can run predictive scenarios with digital twins are capable of determining the outcomes of a storm together with personnel situational unpreparedness and equipment maintenance procrastination. These models help develop effective evacuation, HSE management, and resource allocation policies beforehand. Rather than applying HSE systems during a real emergency, they should be carefully evaluated and challenged beforehand. This minimizes the overall uncertainty during the emergency, thus allowing for an instant, solid response during the real event (Oruh *et al*, 2021; Zhevaga and Morgunov, 2021).

The level of variety separated with Lapse of Time between industries revolves around concepts such as mechanical draws (The Lapse of Time Real weave Bobbin and the Vice it with the pin) and other Industries like Tales and Cosmetics, which may involve the case of lustrous and shining droppings (The Lapse of Time Real weave Bobbin and the Vice it with the pin). The concept of lustrous droppings came from colors such as Golden, Shimmer, platinum droppings, and other colors, which also involve Pinks and are associated with Color Topaz (Lacey Colors). The soft mechanical taps with the case of mechanical draws work with Brushes of Pinks, Whites, and Shimmers (Silver and Gold / Crystal) with Folkay Colorings.

First, doldrums range in all forms of trance and sleepiness while capturing waveforms of rhythm (lucid patterned bars), Graph (Lacey – Cluster). Indications (Lacey – Inandreiss) route accordingly by inserting patterns from Lacey (Pocketed).

Second, within predictive analytics, there is alignment with ISO 45001 frameworks for occupational health and safety predictive modeling and OSHA for general workplace safety, and IMO for marine and offshore operations for all divisions. These frameworks are moving towards a risk-based approach, which requires organizations to identify hazards, assess risk, and take preventive action. Specifically, predictive models fulfill these requirements through organizing and analyzing training, inspection, and incident data to forecast risk, thus syncing operational practice with regulatory compliance (LaCasse *et al*., 2019; Adadey *et al*., 2021).

Predictive models incorporating environmental monitoring inputs to forecast spill potential or emission release not only protect human safety but also align with the predictive paradigm in HSE for compliance with emerging environmental and sustainability protective laws. Such operations fulfill an uncontested sociocultural and policy demand that offshore operations support global climate and sustainability goals with operational safety.

The application of predictive HSE risk models to offshore operations is a major improvement in safety and environmental protection systems. Working with existing HSE systems, predictive models improve real-time analytics and visibility through digital twins. For managers, the models act as decision-support systems with risk prioritization to prepare for maintenance, training, and testing scenarios, as well as for emergencies. From a regulatory standpoint, the offshore operations predictive models highlight evidence of safety ownership by managers, enabling compliance with the ISO 45001, OSHA, and IMO conventions.

Predictive HSE analytics achieve a semblance of reality in the engineering breakthrough of the models. With their implementation, offshore operators do not just react to risks but preemptively assess and eliminate them, resulting in safer workplaces governed by resilient assets and deeper international sustainability compliance. Incorporating predictive risk models into routine offshore operations sets a new industry benchmark in safety management—comprehensive, reactive, and evidence-based (Parhizkar *et al*., 2020; Cheliotis, 2020).

2.5 Challenges and Opportunities

In the context of offshore operations, applying Bayesian Networks (BNs) to predict health, safety, and environmental (HSE) outcomes could be one of the most efficient ways to mitigate the risks associated with one of the most dangerous areas of industry, as shown in Table 2. Yet, there remain big hurdles in the deployment of such models, which limit their borderless utilization and widespread acceptance. Technological innovation and organizational shifts toward digital transformation (Nadkarni and Prügl, 2021; Hanelt *et al*., 2021) provide new sales. At the same time, the exploration of these challenges and possibilities offers a constructive view of the changing landscape to emphasize how BNs could be adapted to become a mainstream blueprint for safety and sustainability in offshore operations.

Table 2: Challenges and Opportunities in Data-Driven Offshore HSE Systems

Category	Key Points	Impact / Implications
Challenges	- Data availability, quality, and interoperability issues across legacy and modern systems. - Organizational resistance to adopting a data-driven safety culture. - Computational complexity of large-scale Bayesian networks or predictive models.	- Limits the accuracy and reliability of predictive safety models. - Slows adoption and integration of advanced HSE analytics. - Requires significant IT and training resources to implement effectively.
Opportunities	- Integration with machine learning and AI for adaptive model updates and improved prediction. - Use of blockchain technology to secure HSE data integrity and traceability. - Potential to extend models to cross-asset offshore ecosystems, including pipelines, rigs, and renewable energy platforms.	- Enhances predictive accuracy and responsiveness of HSE systems. - Builds trust in data and supports regulatory compliance. - Enables holistic risk management across diverse offshore assets.

One especially important challenge comes in the form of data convenience, data availability, including data quality, and data interoperability. Bayesian models require the establishment of relationships by means of datasets as well as the informing by data sets in a more probabilistic manner. For offshore environments, data of this caliber is built and formed from a variety of different streams. These streams could include various forms of sensors, maintenance logs, systems for the monitoring of environments, and assessments of human performance. However, absent data, fragmented recording approaches, and data housed in the undocumented silos of proprietary entities can undermine the data's accuracy and completeness that is required in order to conduct robust modeling. In addition to this, interoperability gaps between legacy systems and digital constructs impede the holistic construction and cohesion of a variety of data sets. This sort of limitation in turn undermines the robustness of Conditional Probability Tables (CPTs) and, subsequently, the entire Bayesian Network (BN).

How many more have shown resistance to the adoption of a data-driven safety culture, rather the its absence is alarming as its second challenge. For as long as it is remembered, offshore projects have worked with and depended on deterministic engineering models and the traditional rule-based procedures for ensuring safety. The shift to data-centric frameworks that are probabilistic in nature is something that goes beyond technical infrastructure, as it transcends culture. The majority of the world's organizations are still rather hesitant and cautious, taking the stance that safety decisions of paramount importance should never be made based on probabilistic means as it clouds the situation, refusing the let the traditional approaches penetrate the area of consideration. This sort of change, as is often the case, is for the most part a reaction to a problem whereby the solution is buried within the deep masked layers of a complex, including the data and privacy exposed levels as a means for undermining norm privacy and the worrying undermined state of the exposed weakness systems.

The third major challenge relates to the computational complexity of large-scale Bayesian networks. With the addition of new interconnected assets to offshore systems—pipelines, rigs, subsea power lines, renewables platforms—the assets are increasing exponentially. These spatially distributed resources, which are expanding over time, encompass larger models, inversely with the amount of time given to solve the problem. Along with the computational paradigm, new optimization techniques are required to track assets with sufficient accuracy. BN cross-asset ecosystems applications can be undermined by the need to circumvent computational time bottlenecks.

On the other hand, detailed and time-sensitive decisions can enhance the effectiveness and impact of Bayesian Networks when forecasting HSE offshore. A promising alternative is to combine Bayes networks with machine learning and artificial intelligence. Machine learning can automatically spot and retrieve actionable patterns from the vast array of sensor information, inspection logs, and operational data, thereby making real-time modifications to the CPTs and enhancing the causal dependencies. With the proper configuration, and depending on how much data is inputted, BNs can become more sophisticated models, thereby improving their predictive ability on offshore HSE forecasting (Marcot and Penman, 2019; Lee *et al.*, 2021). Continuous adaptation to new data is of utmost importance in offshore systems where the environment is unpredictable.

Additional prospects encompass leveraging blockchain technology to secure the confidentiality and integrity of HSE data. Operations offshore create sensitive and vulnerable safety and environmental records, which must be protected from either willful or negligent manipulation. Blockchain-based approaches permit organizations to ascertain the trustworthiness and reliability of data assimilated into BNs as pseudonymized, accountable, transparent, and auditable. Enhancing trust in predictive models and addressing organizational reluctance to probabilistic approaches is another lost value opportunity. Stakeholders can be sure that the forecasts and models' systems are grounded in accurate and validated data, addressing one of the lost value opportunities. Furthermore, smart, blockchain-enabled contracts can automatically enforce safety responses whenever certain thresholds of risk probability are reached, which will further increase organizational resilience.

A third opportunity is the possible extension of Bayesian models from single assets to interrelated cross-asset offshore ecosystems. The offshore industry is evolving toward more interwoven infrastructures in which oil and gas pipelines coexist with offshore wind farms, subsea cables, and floating production platforms. Organizations stand to benefit from expanded BN applications in modeling the interdependencies in these systems to capture cascading trans-asset risks (Lewis, 2019; Wei and Wang, 2020). For example, extreme weather conditions could adversely affect the stability of pipelines, wind turbine foundations, and subsea power transmission systems, creating compounded risks. Cross-asset BN frameworks would enable more integrated resilience-planning approaches, which the Department of Energy

(DOE) and the Department of Homeland Security (DHS) support in critical infrastructure protection.

Although Bayesian Networks can improve offshore HSE forecasting, the full potential is limited by difficulties of data accuracy, acceptance, culture, and computational expansion. At the same time, the growing convergence of Machine Learning, blockchain data verification, and cross-asset modeling serves as potential growth points. Addressing the identified barriers will require an integrated approach across the technical, organizational, and policy domains to ensure that the scientific rigor of Bayesian Networks is matched with practicality and trust in real-world applications. It is this set of challenges, combined with the rapid growth points, that can establish Bayesian Networks at the core of the next generation offshore HSE management—one that is resilient, anticipatory, and incorporates the complexities of the offshore energy systems' sustainability.

3. Conclusion

HSE analytics are advanced and predictive in nature for the offshore oil and gas industry. These analytics shift the paradigm from reactive to proactive and from simplistic to advanced safety management. Traditionally, safety strategies across the oil and gas and the renewable energy industries are heavily dominated by incident reporting and post-event inquiries. Although useful, these strategies are always retrospective and reactive in nature, often identifying risks only after the collapse of a system. Predictive analytics, on the other hand, transforms offshore risk management by predicting accidents and then developing strategies to avoid them.

The transformation is driven by the use of Bayesian Networks. These networks, like other graphic or probabilistic methods, model the uncertain likelihood of accidents given offshore accidents and their appropriate Bayesian populations and origins. As predictive environments, these offshore environments are characterized by the interdependencies of humans, their technical systems, and the geo-physical nature of the environment. These networks model interdependencies by integrating quantitative data and qualitative expert opinions. The outcome is the computation of risks not only through their predictive surge, but through the routes of risk and safe pathways, their advocacy, steering operators to the most holistic model to use.

Importing other sources of data—such as training data, logbooks, accident databases, and reports of near-misses—strengthens the predictive models. These factors, collectively, offer all-encompassing operational risk analyses that highlight the lack of competence, equipment, and backbone of the systemic safety culture, siloed and decoupled. A holistic view of operational risk analysis enables advanced forecasting, which augments risk prioritization. Because faults and lapses that curb safety performance can be addressed from various possible angles, maintenance and repair strategies, along with bespoke training, can be instituted.

The far-reaching effects of predictive HSE analytics are profound. It not only augments accident prevention mechanisms but also enables adherence to international regulatory standards on environmental and safety compliance. Predictive analytics ensures offshore operators remain safety innovators with resilient, sustainable operations amid growing environmental and technical problems.

4. References

1. Ojo AA, Ayo TE. Examining the need to regulate health, safety, and environmental (HSE) concerns of offshore wind energy development in the United Kingdom. Madonna Univ Niger Fac Law J. 2021;7.
2. Brkić D, Praks P. Probability analysis and prevention of offshore oil and gas accidents: fire as a cause and a consequence. Fire. 2021;4(4):71.
3. Akashraj DP, Maleith KD. The impact of ageing facilities on oil production in South Sudan. Int J Res Rev. 2020;7(11):312-35.
4. Giannopoulos N. Global environmental regulation of offshore energy production: searching for legal standards in ocean governance. Rev Eur Comp Int Environ Law. 2019;28(3):289-303.
5. Roos P. Policy change in offshore decommissioning governance: dealing with environmental politics and coping with ecological uncertainty. A comparative study of offshore oil and gas in the Dutch North Sea and Australian Commonwealth Waters [dissertation]. Wageningen: Wageningen University; 2019.
6. Gann GD, McDonald T, Walder B, Aronson J, Nelson CR, Jonson J, et al. International principles and standards for the practice of ecological restoration. Restor Ecol. 2019;27(S1):S1-S46.
7. Arnal-Velasco D, Barach P. Anaesthesia and perioperative incident reporting systems: opportunities and challenges. Best Pract Res Clin Anaesthesiol. 2021;35(1):93-103.
8. Niu Y, Lu W, Xue F, Liu D, Chen K, Fang D, et al. Towards the “third wave”: an SCO-enabled occupational health and safety management system for construction. Saf Sci. 2019;111:213-23.
9. Chenoweth E, English R, Gofas A, Kalyvas SN, editors. The Oxford handbook of terrorism. Oxford: Oxford University Press; 2019.
10. Zhou Z, Li C, Mi C, Qian L. Exploring the potential use of near-miss information to improve construction safety performance. Sustainability. 2019;11(5):1264.
11. Cantelmi R, Di Gravio G, Patriarca R. Reviewing qualitative research approaches in the context of critical infrastructure resilience. Environ Syst Decis. 2021;41(3):341-76.
12. Council GWE. GWEC global wind report 2021. Brussels: Global Wind Energy Council; 2021. p. 80.
13. Kelleher JD, Mac Namee B, D'arcy A. Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies. Cambridge: MIT Press; 2020.
14. Sarker IH. Machine learning: algorithms, real-world applications and research directions. SN Comput Sci. 2021;2(3):160.
15. Sarkar S, Vinay S, Raj R, Maiti J, Mitra P. Application of optimized machine learning techniques for prediction of occupational accidents. Comput Oper Res. 2019;106:210-24.
16. Ajayi A, Oyedele L, Davila Delgado JM, Akanbi L, Bilal M, Akinade O, et al. Big data platform for health and safety accident prediction. World J Sci Technol Sustain Dev. 2019;16(1):2-21.
17. Raja U, Iqbal N. Ensuring worker safety in Lahore’s large industries: a study on occupational health, safety, and risk management. J Energy Environ Policy Options.

2019;2(4):117-24.
18. Thomas E, Brown J. Using feedback to improve accountability in global environmental health and engineering. Environ Sci Technol. 2020;55(1):90-9.
19. Levin LA, Bett BJ, Gates AR, Heimbach P, Howe BM, Janssen F, et al. Global observing needs in the deep ocean. Front Mar Sci. 2019;6:241.
20. Jahanbakht M, Xiang W, Hanzo L, Azghadi MR. Internet of underwater things and big marine data analytics—a comprehensive survey. IEEE Commun Surv Tutor. 2021;23(2):904-56.
21. Adebisi B, Aigbedion E, Ayorinde OB, Onukwulu EC. A conceptual model for predictive asset integrity management using data analytics to enhance maintenance and reliability in oil & gas operations. Int J Multidiscip Res Growth Eval. 2021;2(1):534-54.
22. Nguyen T, Gosine RG, Warrian P. A systematic review of big data analytics for oil and gas industry 4.0. IEEE Access. 2020;8:61183-201.
23. Trenerry B, Chng S, Wang Y, Suhaila ZS, Lim SS, Lu HY, et al. Preparing workplaces for digital transformation: an integrative review and framework of multi-level factors. Front Psychol. 2021;12:620766.
24. Scholz RW, Czichos R, Parycek P, Lampoltshammer TJ. Organizational vulnerability of digital threats: a first validation of an assessment method. Eur J Oper Res. 2020;282(2):627-43.
25. Chandrasegaran D, Ghazilla RAR, Rich K. Human factors engineering integration in the offshore O&G industry: a review of current state of practice. Saf Sci. 2020;125:104627.
26. Hameed H, Bai Y, Ali L. A risk-based inspection planning methodology for integrity management of subsea oil and gas pipelines. Ships Offshore Struct. 2021;16(7):687-99.
27. Amaechi CV, Gillett N, Odijie AC, Hou X, Ye J. Composite risers for deep waters using a numerical modelling approach. Compos Struct. 2019;210:486-99.
28. Aivaliotis P, Arkouli Z, Georgoulias K, Makris S. Degradation curves integration in physics-based models: towards the predictive maintenance of industrial robots. Robot Comput Integr Manuf. 2021;71:102177.
29. Dindar S, Kaewunruen S, An M, Sussman JM. Bayesian network-based probability analysis of train derailments caused by various extreme weather patterns on railway turnouts. Saf Sci. 2018;110:20-30.
30. Reder M, Yürüşen NY, Melero JJ. Data-driven learning framework for associating weather conditions and wind turbine failures. Reliab Eng Syst Saf. 2018;169:554-69.
31. Du Y, Liu Y, Wang X, Fang J, Sheng G, Jiang X. Predicting weather-related failure risk in distribution systems using Bayesian neural network. IEEE Trans Smart Grid. 2020;12(1):350-60.
32. Renga D, Apiletti D, Giordano D, Nisi M, Huang T, Zhang Y, et al. Data-driven exploratory models of an electric distribution network for fault prediction and diagnosis. Computing. 2020;102(5):1199-211.
33. Skliris N, Marsh R, Srokosz M, Aksenov Y, Rynders S, Fournier N. Assessing extreme environmental loads on offshore structures in the North Sea from high-resolution ocean currents, waves and wind forecasting. J Mar Sci Eng. 2021;9(10):1052.
34. Jimenez-Martinez M. Harbor and coastal structures: a review of mechanical fatigue under random wave loading. Heliyon. 2021;7(10).
35. Jagoda K, Wojcik P. Implementation of risk management and corporate sustainability in the Canadian oil and gas industry: an evolutionary perspective. Account Res J. 2019;32(3):381-98.
36. Döring S, Drobetz W, El Ghoul S, Guedhami O, Schröder H. Foreign institutional investors, legal origin, and corporate greenhouse gas emissions disclosure. J Bus Ethics. 2020.
37. Mentes A, Turan O. A new resilient risk management model for offshore wind turbine maintenance. Saf Sci. 2019;119:360-74.
38. Pedersen S, Ahsan D. Emergency preparedness and response: insights from the emerging offshore wind industry. Saf Sci. 2020;121:516-28.
39. Mahesh K. Accident modelling and uncertainty assessment in risk and reliability quantifications to support new technology system using Bayesian approach. 2020.
40. Kodoth MM, Shibutani T. Accident modelling and uncertainty assessment in risk and reliability quantifications to support new technology system using Bayesian approach. 2019.
41. Fabianoa B, Pettinatoa M, Reverberib AP, Curròa F. Human factors and safety management: a field study on safety performance in the process industry. Chem Eng. 2019;77.
42. Raza MA, Salehi S, Ghazal S, Ybarra VT, Naqvi SAM, Cokely ET, et al. Situational awareness measurement in a simulation-based training framework for offshore well control operations. J Loss Prev Process Ind. 2019;62:103921.
43. Bernard J, Hutter M, Reinemuth H, Pfeifer H, Bors C, Kohlhammer J. Visual-interactive preprocessing of multivariate time series data. Comput Graph Forum. 2019;38(3):401-12.
44. Qing X, Li W, Wang Y, Sun H. Piezoelectric transducer-based structural health monitoring for aircraft applications. Sensors. 2019;19(3):545.
45. Ossai CI. A data-driven machine learning approach for corrosion risk assessment—a comparative study. Big Data Cogn Comput. 2019;3(2):28.
46. Nelson J, Dyer AS, Romeo LF, Wenzlick MZ, Zaengle D, Duran R, et al. Evaluating offshore infrastructure integrity. Pittsburgh: National Energy Technology Laboratory; 2021. Report No.: DOE/NETL-2021/2643.
47. Moosavi S, Samavatian MH, Parthasarathy S, Teodorescu R, Ramnath R. Accident risk prediction based on heterogeneous sparse data: new dataset and insights. In: Proceedings of the 27th ACM SIGSPATIAL international conference on advances in geographic information systems; 2019. p. 33-42.
48. Schlögl M, Stütz R, Laaha G, Melcher M. A comparison of statistical learning methods for deriving determining factors of accident occurrence from an imbalanced high resolution dataset. Accid Anal Prev. 2019;127:134-49.
49. Bhattacharya A, Ivanyna M, Oman W, Stern N. Climate action to unlock the inclusive growth story of the 21st century. 2021.
50. Alabi AA, Amoo OO, Ike CC, Bolatito A. Developing a vendor risk assessment model to secure supply chains in US and Canadian markets. 2021.
51. Hoerl RW, Snee RD. Statistical thinking: improving business performance. Hoboken: John Wiley & Sons;

2020.
52. Schölkopf B, Locatello F, Bauer S, Ke NR, Kalchbrenner N, Goyal A, et al. Toward causal representation learning. Proc IEEE. 2021;109(5):612-34.
53. Alkhairy IH. Designing and encoding scenario-based expert elicitation for large conditional probability tables. 2020.
54. Azar A, Dolatabad KM. A method for modelling operational risk with fuzzy cognitive maps and Bayesian belief networks. Expert Syst Appl. 2019;115:607-17.
55. Pirbhulal S, Gkioulos V, Katsikas S. Towards integration of security and safety measures for critical infrastructures based on Bayesian networks and graph theory: a systematic literature review. Signals. 2021;2(4):771-802.
56. Sheehan B, Murphy F, Mullins M, Ryan C. Connected and autonomous vehicles: a cyber-risk classification framework. Transp Res Part A Policy Pract. 2019;124:523-36.
57. Hasan R, Chatwin C, Sayed M. Examining alternatives to traditional accident causation models in the offshore oil and gas industry. J Risk Res. 2020;23(9):1242-57.
58. Amirafshari P. Optimising non-destructive examination of newbuilding ship hull structures by developing a data-centric risk and reliability framework based on fracture mechanics. 2019.
59. Abideen AZ, Sundram VPK, Pyeman J, Othman AK, Sorooshian S. Food supply chain transformation through technology and future research directions—a systematic review. Logistics. 2021;5(4):83.
60. Oruh ES, Mordi C, Dibia CH, Ajonbadi HA. Exploring compassionate managerial leadership style in reducing employee stress level during COVID-19 crisis: the case of Nigeria. Empl Relat. 2021;43(6):1362-81.
61. Zhevaga A, Morgunov A. Integrated risk measurement system in commercial bank. In: Risk assessment and financial regulation in emerging markets' banking: trends and prospects. Cham: Springer International Publishing; 2021. p. 225-50.
62. LaCasse PM, Otieno W, Maturana FP. A survey of feature set reduction approaches for predictive analytics models in the connected manufacturing enterprise. Appl Sci. 2019;9(5):843.
63. Adadey A, Giannini R, Possanza LB. Developing an analytical pipeline to classify patient safety event reports using optimized predictive algorithms. Methods Inf Med. 2021;60(05/06):147-61.
64. Parhizkar T, Hogenboom S, Vinnem JE, Utne IB. Data driven approach to risk management and decision support for dynamic positioning systems. Reliab Eng Syst Saf. 2020;201:106964.
65. Cheliotis MF. A compound novel data-driven and reliability-based predictive maintenance framework for ship machinery systems. 2020.
66. Nadkarni S, Prügl R. Digital transformation: a review, synthesis and opportunities for future research. Manag Rev Q. 2021;71(2):233-41.
67. Hanelt A, Bohnsack R, Marz D, Antunes Marante C. A systematic review of the literature on digital transformation: insights and implications for strategy and organizational change. J Manag Stud. 2021;58(5):1159-97.
68. Mahanti R. Data quality: dimensions, measurement, strategy, management, and governance. Milwaukee: Quality Press; 2019.
69. Gliklich R, Leavy M, Dreyer N. Tools and technologies for registry interoperability, registries for evaluating patient outcomes: a user's guide, addendum 2. Rockville: Agency for Healthcare Research and Quality; 2019. AHRQ Publication No. 19(20)-EHC017-EF.
70. Marcot BG, Penman TD. Advances in Bayesian network modelling: integration of modelling technologies. Environ Model Softw. 2019;111:386-93.
71. Lee R, Venieris SI, Lane ND. Deep neural network–based enhancement for image and video streaming systems: a survey and future directions. ACM Comput Surv. 2021;54(8):1-30.
72. Lewis TG. Critical infrastructure protection in homeland security: defending a networked nation. Hoboken: John Wiley & Sons; 2019.
73. Wei W, Wang J. Modeling and optimization of interdependent energy infrastructures. Cham: Springer; 2020.
74. Enemosah A. Intelligent decision support systems for oil and gas control rooms using real-time AI inference. Int J Eng Technol Res Manag. 2021;5(12):236-44.
75. Marcus LJ, McNulty EJ, Flynn LB, Henderson JM, Neffenger PV, Serino R, et al. The POP-DOC loop: a continuous process for situational awareness and situational action. Ind Mark Manag. 2020;88:272-7.
76. Kosmowski K, Gołębiewski D. Functional safety and cyber security analysis for life cycle management of industrial control systems in hazardous plants and oil port critical infrastructure including insurance. J Pol Saf Reliab Assoc. 2019;10.
77. Yakoot MS, Elgibaly AA, Ragab AM, Mahmoud O. Well integrity management in mature fields: a state-of-the-art review on the system structure and maturity. J Pet Explor Prod. 2021;11(4):1833-53.
78. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. Systematic review of non-destructive testing methods for predictive failure analysis in mechanical systems. IRE J. 2020;4(4):207-15.
79. Grace EO, John A. Recent advances in non-destructive testing of concretes and structures: an outlook. J Civ Eng Constr Technol. 2019;10(3):20-31.
80. Bugalia N, Maemura Y, Ozawa K. A system dynamics model for near-miss reporting in complex systems. Saf Sci. 2021;142:105368.
81. Banerjee S, Santos J, Hempel M, Ghasemzadeh P, Sharif H. A novel method of near-miss event detection with software defined radar in improving railyard safety. Safety. 2019;5(3):55.
82. Hagenlocher M, Thieken A, Schneiderbauer S, Ayerbe IA, Dobes P, Donovan A, et al. Risk assessment. In: Science for disaster risk management 2020: acting today, protecting tomorrow. Luxembourg: Publications Office of the European Union; 2020. p. 54-65.
83. Yang Y. Reforming health, safety, and environmental regulation for offshore operations in China: risk and resilience approaches? Sustainability. 2019;11(9):2608.
84. Eyinade W, Ezeilo OJ, Ogundeji IA. An internal compliance framework for evaluating financial system integrity under changing regulatory environments. 2021.
85. Behnassi M, Gupta H, Ramachandran N, Winniefridah M, Ramachandran G, Lakeman S, et al. Effectiveness of disaster risk governance and resilience building:

linkages, knowledge, inclusiveness, and regulation. In: Social-ecological systems (SES) from risks and insecurity to viability and resilience. Cham: Springer International Publishing; 2021. p. 1-37.
86. Farmanbar M, Rong C. Triangulum city dashboard: an interactive data analytic platform for visualizing smart city performance. Processes. 2020;8(2):250.
87. Shirowzhan S, Sepasgozar SM, Trinder J. Developing metrics for quantifying buildings' 3D compactness and visualizing point cloud data on a web-based app and dashboard. J Constr Eng Manag. 2021;147(3):04020178.
88. Schlögl M. A multivariate analysis of environmental effects on road accident occurrence using a balanced bagging approach. Accid Anal Prev. 2020;136:105398.
89. Norris MB, Moore GM. How tree risk assessment methods work: sensitivity analyses of sixteen methods reveal the value of quantification and the impact of inputs on risk ratings. Arboric Urban For. 2020;46(6):402-31.
90. Zhu P, Liyanage JP. Cybersecurity of offshore oil and gas production assets under trending asset digitalization contexts: a specific review of issues and challenges. Eur J Secur Res. 2021;6(2):125-49.
91. Wu J, Lind M, Zhang X, Pardhasaradhi K, Pathi SK, Myllerup CM. Knowledge acquisition and representation for intelligent operation support in offshore fields. Process Saf Environ Prot. 2021;155:415-43.
92. Mantini M, Celiento D, Scalabrini M. ENI innovative approach to HSE integrated management system (IMS) to enhance sustainability values. In: Offshore Mediterranean Conference and Exhibition; 2019 Mar. p. OMC-2019.
93. Obaid HS, Dheyab SA, Sabry SS. The impact of data pre-processing techniques and dimensionality reduction on the accuracy of machine learning. In: 2019 9th annual information technology, electromechanical engineering and microelectronics conference (IEMECON); 2019 Mar. p. 279-83.
94. Williams T, Haut R, Cohen J, Pettigrew J. 21st century ocean energy safety research roadmap. In: Offshore Technology Conference; 2019 Apr. p. D022S057R010.
95. Nezamian A, Kartsounis M. Risk-informed asset management framework for aged port facilities against potential external hazards. In: ISOPE International Ocean and Polar Engineering Conference; 2019 Jun. p. ISOPE-I.
96. Simpson G, FitzGerald F, Taylor S. Major accident hazards–own your barrier. In: SPE Offshore Europe Conference and Exhibition; 2019 Sep. p. D011S001R005.
97. Kumar KN, Mackenzie B, Løken KH. Using advanced analytics to identify the most probable locations of corrosion under insulation. In: SPE Offshore Europe Conference and Exhibition; 2019 Sep. p. D021S008R003.
98. Atia M, Keys M, Omar T. Real-time structural risk assessment for offshore asset management. In: Abu Dhabi International Petroleum Exhibition and Conference; 2019 Nov. p. D011S011R003.
99. Hamedifar H, Wilczynski H. Planning for unknown in the new age of digital: a paradigm for offshore oil and gas risk assessment and management. In: Offshore Technology Conference; 2021 Aug. p. D031S041R007.