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## A Predictive Analytics Model for Minimizing Unplanned Downtime in Subsea and FPSO Oilfield Infrastructure

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### Abstract

Unplanned downtime in offshore oilfield infrastructure, particularly in subsea systems and Floating Production Storage and Offloading (FPSO) units, poses significant operational, safety, and economic challenges. These complex systems operate in remote and harsh environments, where failure of critical components can lead to prolonged outages, costly repairs, and production losses. Traditional reactive or time-based maintenance strategies are often inadequate for preventing unexpected equipment failures in such settings. To address this gap, this study proposes a predictive analytics model designed to forecast potential failures and minimize unplanned downtime in subsea and FPSO infrastructure. The model integrates real-time and historical operational data—such as pressure, temperature, vibration, and flow rate—using advanced machine learning techniques including anomaly detection and time-series forecasting. A layered architecture is developed, comprising data acquisition, preprocessing, predictive modeling, and decision-support components. Key performance indicators (KPIs) such as downtime probability, equipment health scores, and maintenance urgency indices are derived to guide operational decisions. The predictive model is validated through a case study involving a representative offshore production system, demonstrating its ability to detect early signs of equipment degradation and recommend timely interventions. The results indicate significant potential for improving maintenance efficiency, enhancing asset reliability, and reducing production losses due to unplanned events. In addition to technical design, the study addresses practical implementation considerations including data integration challenges, model training, and real-time alert mechanisms. The model also emphasizes scalability and adaptability across different offshore asset configurations. This research highlights the strategic importance of predictive analytics in transitioning offshore oil and gas operations from reactive to proactive asset management. It contributes to advancing digital transformation in offshore production systems, promoting safer, more resilient, and cost-effective operations in high-risk deepwater environments.

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### 1. Introduction

In offshore oil and gas operations, maintaining continuous production—referred to as uptime—is critical to achieving operational efficiency, maximizing asset value, and ensuring financial viability (Awe, 2017; Oyedokun, 2019). The economic implications of downtime are significant, with every hour of lost production in deepwater environments potentially costing hundreds of thousands of dollars. Moreover, unplanned interruptions can compromise safety, accelerate equipment degradation, and increase the likelihood of environmental incidents (Awe *et al.*, 2017; ADEWOYIN *et al.*, 2020). As the industry continues to explore and develop hydrocarbon reserves in increasingly remote and complex environments, the demand for robust uptime assurance mechanisms has become more urgent than ever (Akpan *et al.*, 2017; OGUNNOWO *et al.*, 2020). Predictive analytics has emerged as a transformative tool in achieving proactive maintenance and reducing unplanned downtime.

Unlike traditional maintenance strategies that rely on fixed schedules or reactive interventions, predictive analytics enables condition-based decision-making (Omisola *et al.*, 2020; ADEWOYIN *et al.*, 2020). It leverages real-time sensor data, historical failure records, and advanced machine learning algorithms to detect anomalies, forecast equipment degradation, and anticipate failures before they occur (Solanke *et al.*, 2014; Chudi *et al.*, 2019). This approach not only enhances reliability but also optimizes maintenance resources and minimizes production disruptions. In offshore settings where logistics are complex and access to equipment is limited, predictive maintenance supported by analytics can significantly improve asset lifecycle management and operational safety (Magnus *et al.*, 2011; Chudi *et al.*, 2019). Despite these benefits, applying predictive analytics in offshore environments—particularly for subsea systems and Floating Production Storage and Offloading (FPSO) units—presents unique challenges. Subsea systems operate under extreme conditions, including high pressure, low temperatures, and limited accessibility, which constrain sensor deployment and data transmission (Awe *et al.*, 2017; Akpan *et al.*, 2019). Similarly, FPSOs integrate a wide range of processing, storage, and offloading operations, often with aging infrastructure and diverse equipment types that complicate monitoring and diagnostics. Additionally, the dynamic marine environment subjects these systems to mechanical stresses and environmental fluctuations that further increase failure risks (Ajiga, 2021; Odio *et al.*, 2021). This study aims to develop and present a predictive analytics model specifically designed to address the complexities of subsea and FPSO oilfield infrastructure. The model focuses on minimizing unplanned downtime by enabling early detection of abnormal behavior and providing actionable insights for maintenance planning. It incorporates real-time and historical data from critical operational parameters—such as temperature, pressure, vibration, and flow rate—and applies machine learning techniques to assess equipment health and forecast potential failures. The scope of the model spans data acquisition, preprocessing, model training, and integration with decision-support systems, emphasizing its adaptability to different offshore configurations and technologies.

The proposed model seeks to bridge the gap between offshore operational realities and the potential of digital transformation. By integrating predictive analytics into the core of asset management strategies, the model contributes to enhancing production continuity, reducing operational costs, and improving safety margins (Tasleem *et al.*, 2020; Adesemoye *et al.*, 2021; ADEWOYIN *et al.*, 2021). This outlines the technical architecture, implementation methodology, and validation results of the model through a case study representative of real-world FPSO and subsea operations. It also discusses the limitations, challenges, and future opportunities associated with applying predictive analytics in offshore oil and gas production.

## 2. Methodology

For the development of a predictive analytics model aimed at minimizing unplanned downtime in subsea and Floating Production Storage and Offloading (FPSO) oilfield infrastructure, a systematic literature review was conducted using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. This approach ensured a comprehensive, transparent, and replicable process

in identifying, selecting, and analyzing relevant research and technological developments.

The review began with a structured search across multiple databases including Scopus, IEEE Xplore, Web of Science, and ScienceDirect, targeting peer-reviewed journal articles, industry reports, and conference proceedings published between 2000 and 2024. Keywords and Boolean combinations such as “predictive analytics,” “unplanned downtime,” “subsea systems,” “FPSO,” “machine learning in offshore oil,” and “condition-based maintenance” were employed to capture a broad yet relevant scope of literature. Duplicates were removed using citation management software to streamline the review process.

Inclusion criteria were defined to focus on studies that proposed, implemented, or evaluated predictive models or data-driven maintenance strategies within offshore oil and gas contexts, particularly targeting subsea infrastructure or FPSO units. Studies solely focused on terrestrial or shallow-water facilities, as well as those lacking empirical data or methodological clarity, were excluded. The remaining records were subjected to a two-stage screening process: an initial review of titles and abstracts, followed by a full-text analysis to ensure alignment with the research objective.

Data from the selected studies were extracted using a standardized form capturing information on modeling techniques, data sources, algorithm performance, types of equipment addressed, and implementation outcomes. Studies were also evaluated for methodological rigor, reproducibility, and relevance to real-world offshore operations. Discrepancies in study eligibility or data interpretation were resolved through consensus among the reviewers.

The PRISMA flow diagram documented the entire selection process, including the number of records identified, screened, excluded, and included in the final analysis. The synthesis of findings emphasized common predictive techniques—such as regression models, support vector machines, neural networks, and hybrid systems—as well as the importance of data quality, sensor integration, and real-time analytics. The review also identified significant research gaps, particularly in the application of predictive models to integrated subsea-FPSO systems under variable operational and environmental conditions.

This PRISMA-based methodology provided a robust foundation for developing a comprehensive predictive analytics model, highlighting best practices, technological enablers, and future directions. The systematic approach ensured that the resulting model would be informed by the latest evidence and capable of addressing the pressing challenge of unplanned downtime in complex offshore oilfield infrastructure.

### 2.1 Literature review

Unplanned downtime in offshore oil and gas production remains one of the most critical challenges faced by operators, particularly in subsea systems and Floating Production Storage and Offloading (FPSO) units (OGUNNOWO *et al.*, 2021; Ogunnowo *et al.*, 2021). These platforms operate in complex environments where asset failures can lead to substantial financial losses, safety risks, and environmental hazards. A growing body of literature has sought to understand the causes of such downtime, evaluate existing maintenance strategies, and explore innovative technologies—particularly data analytics and machine learning—to improve asset reliability and performance.

(Tasleem *et al.*, 2020).

The causes of unplanned downtime in subsea systems and FPSOs are multifactorial and often interrelated. Subsea components—including wellheads, manifolds, pipelines, risers, and control umbilicals—are exposed to high-pressure, low-temperature conditions that accelerate wear and corrosion. Common failure modes include hydraulic leaks, sensor malfunction, blockage from hydrate formation, and structural fatigue. Similarly, FPSO topside systems house complex processing equipment, including separators, compressors, pumps, and control systems. Failures often stem from mechanical breakdowns, control system anomalies, instrumentation faults, and equipment aging (ADEWOYIN *et al.*, 2021; OGUNNOWO *et al.*, 2021). Literature emphasizes that inadequate early fault detection, insufficient system redundancy, and delays in maintenance mobilization contribute significantly to downtime events in both systems.

Conventional monitoring approaches in offshore infrastructure involve periodic inspections, preventive maintenance schedules, and reactive interventions. These practices, while standard, often fall short in detecting early-stage faults or capturing fast-developing anomalies. Preventive maintenance can lead to unnecessary servicing or miss failures occurring outside scheduled intervals. Meanwhile, condition-based monitoring (CBM) has gained traction, using sensor feedback to inform maintenance actions. However, in many cases, CBM lacks the predictive capabilities to forecast future failures, especially in highly integrated systems like FPSOs (Okolo *et al.*, 2021; Ojika *et al.*, 2021). The effectiveness of these traditional practices is limited by sensor accessibility, data latency, and inconsistent failure data.

The economic cost of unplanned downtime in deepwater fields is substantial, often exceeding \$1 million per incident when accounting for production losses, mobilization of repair vessels, and delayed shipments. FPSOs, which operate as self-contained production and storage units, are particularly vulnerable; if one critical component fails, the entire operation may be forced to shut down. Downtime also exacerbates safety risks, particularly when failures involve high-pressure systems, flammable materials, or loss of containment. Furthermore, emergency maintenance operations in offshore conditions carry significant safety hazards for personnel and increase the likelihood of environmental non-compliance due to oil discharges or gas flaring (Darajimba *et al.*, 2021; Orieno *et al.*, 2021). The literature increasingly recognizes that improving uptime is not merely a matter of efficiency but also a cornerstone of offshore safety and environmental performance.

Recent years have seen a surge in the application of advanced data analytics and machine learning techniques in industrial asset management. Predictive analytics, using supervised and unsupervised learning models, has shown promise in forecasting equipment degradation and identifying potential faults before they result in failure. Techniques such as support vector machines (SVM), decision trees, neural networks, and time-series forecasting models (e.g., ARIMA, LSTM) have been employed to interpret operational data and

derive health indicators for critical equipment.

Digital twins and edge computing are further enabling real-time simulation and localized decision-making, especially valuable in offshore environments where communication with onshore facilities may be constrained. Additionally, integrated platforms combining IoT-based sensors, cloud analytics, and machine learning have demonstrated improved fault detection and diagnostics, supporting more effective maintenance planning and resource allocation (Onaghinor *et al.*, 2021; Mustapha *et al.*, 2021).

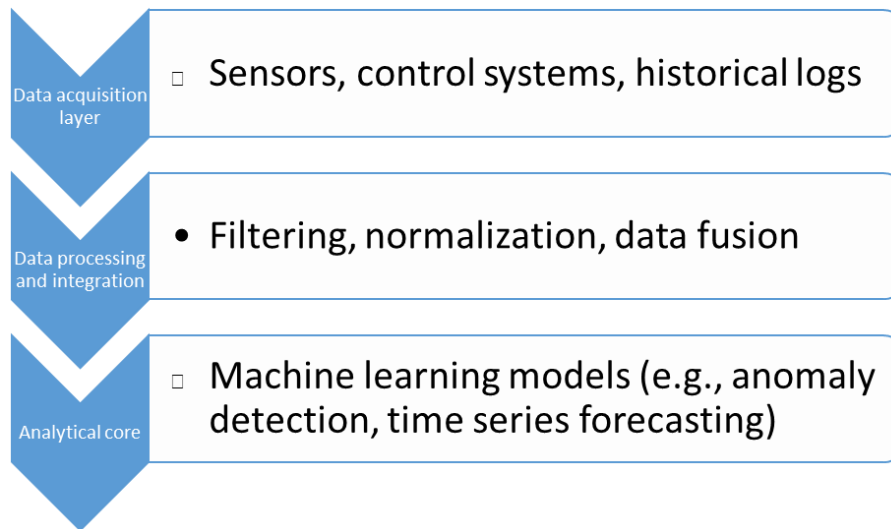
Despite these technological advances, few models in the literature are specifically tailored to the unique challenges of offshore and deepwater environments. Most focus on general manufacturing or land-based process industries, indicating a gap in offshore-specific predictive frameworks that account for subsea constraints, marine dynamics, and complex process interdependencies.

The literature underscores the high stakes of unplanned downtime in offshore oil production, the limitations of existing maintenance practices, and the emerging role of predictive analytics in improving system reliability (Adewoyin, 2021; Dienagha *et al.*, 2021). However, a targeted predictive model for subsea and FPSO systems remains an underexplored research avenue—one this study seeks to address.

## 2.2 Subsea and FPSO Infrastructure Overview

Subsea production systems and Floating Production Storage and Offloading (FPSO) units form the backbone of deepwater oil and gas developments as shown in figure 1. These infrastructures enable hydrocarbon extraction, processing, and export in remote offshore locations, often under extreme environmental and operational conditions. A clear understanding of their architecture, interdependencies, and associated data challenges is critical for improving reliability, minimizing unplanned downtime, and supporting predictive analytics implementation (Chudi *et al.*, 2021; Awe, 2021).

Subsea infrastructure includes a variety of critical components designed to extract and transport hydrocarbons from the seabed to surface facilities. Key elements begin with subsea wells, which are drilled into the reservoir and equipped with subsea trees that manage the flow of oil and gas. These wells are connected via subsea manifolds, which collect and route production from multiple wells into a common flow path. The manifolds also house valves and control systems for flow distribution, pressure regulation, and well isolation. From the manifolds, production flows through flowlines—rigid or flexible pipes laid on or buried beneath the seabed—which transport fluids to riser bases or directly to surface facilities. Risers connect the seabed flowlines to the FPSO and accommodate the dynamic motions of the floating vessel while maintaining flow integrity. At the surface, the FPSO topside systems include separators, compressors, pumps, heaters, and other process equipment necessary for oil, gas, and water separation, gas compression, and export readiness. The FPSO also contains storage tanks and offloading systems to transfer processed oil to shuttle tankers.



**Fig 1:** Predictive Analytics Model Architecture

These components form a highly integrated production network, with strong operational interdependencies. A failure in any part—whether a blocked flowline, a malfunctioning subsea valve, or a faulty FPSO pump—can disrupt the entire production chain. For example, hydrate formation in a subsea flowline can lead to flow blockage, forcing a shutdown upstream at the well and downstream at the riser or topside process system. Similarly, topside equipment failures such as high-pressure separators exceeding operational limits can trigger emergency shut-ins, impacting subsea operations. The coupling of mechanical, electrical, hydraulic, and control systems across subsea and surface domains increases the complexity of failure modes. These include corrosion, fatigue, vibration-induced damage, scaling, erosion, and control system malfunctions. The integrated nature of the infrastructure demands a system-level understanding of performance and degradation patterns to ensure timely interventions.

One of the primary barriers to effective monitoring and proactive maintenance in these systems is data availability and telemetry challenges. The subsea environment is harsh, remote, and often lacks the extensive sensing coverage found in onshore facilities. Traditional sensors must be specially designed to withstand high pressures, low temperatures, and corrosive seawater. Deployment of sensors on subsea wells, manifolds, and flowlines is expensive and technically constrained by accessibility and reliability concerns. Moreover, the power supply and data transmission capabilities of subsea instrumentation are limited, restricting real-time monitoring across the entire network. Communication from subsea equipment to topside control rooms is typically achieved via umbilicals or acoustic telemetry, both of which have bandwidth and latency limitations (Woodhouse *et al.*, 2018; Sotoodeh *et al.*, 2019). On the FPSO side, although more extensive sensing and automation systems are present, they often operate in siloed subsystems with limited integration across departments. This segmentation of data—between process control, condition

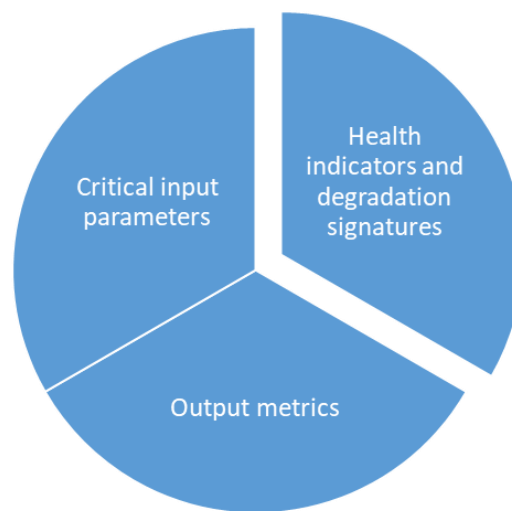
monitoring, and safety systems—reduces visibility into the entire production chain. The combination of high-volume data generation and offshore bandwidth constraints also poses difficulties for real-time data analytics and decision-making.

Efforts to address these telemetry issues are ongoing, including the use of edge computing, subsea wireless networks, and integration of data historians with cloud-based platforms. However, to fully enable predictive maintenance and minimize unplanned downtime, a comprehensive, interoperable data infrastructure is needed. This would support cross-domain visibility, real-time diagnostics, and AI-based decision support tools that span both subsea and topside systems.

The architecture of subsea and FPSO infrastructure is intricate and interdependent, involving numerous components operating under harsh and dynamic conditions. Understanding the interrelated failure mechanisms and overcoming telemetry challenges are essential steps toward improving asset integrity and production efficiency. Leveraging advanced data integration and predictive technologies can unlock significant value by reducing unplanned shutdowns and extending the operational life of offshore production systems (Lee *et al.*, 2020; Hoffmann *et al.*, 2020).

### 2.3 Predictive Analytics Model Architecture

The architecture of a predictive analytics model for offshore oil and gas systems must accommodate the harsh, data-constrained environment of subsea and Floating Production Storage and Offloading (FPSO) platforms, while enabling high-resolution diagnostics and early fault detection. A robust architecture involves four primary components: the data acquisition layer, data processing and integration, the analytical core, and the output layer as shown in figure 2 (Paik *et al.*, 2019; Mrabet *et al.*, 2020). Together, these components enable the transition from raw operational data to actionable insights that minimize unplanned downtime.



**Fig 2:** Model Inputs and Key Performance Indicators (KPIs)

The foundation of the predictive analytics model is built on comprehensive and continuous data acquisition from key subsea and topside systems. This includes physical sensors deployed across critical components such as pumps, compressors, valves, risers, separators, and subsea manifolds. Typical sensor data types include pressure, temperature, vibration, flow rate, acoustic emissions, and corrosion monitoring. These sensors are integrated with supervisory control and data acquisition (SCADA) systems and distributed control systems (DCS), which collect and relay real-time process information.

In addition to live sensor feeds, historical maintenance logs, failure records, and operator inputs are incorporated into the dataset to provide context and support supervised learning approaches. These legacy data sources enhance model training by offering labeled examples of past fault patterns and system responses, which are essential for robust predictive modeling (Flath and Stein, 2018; Shafique *et al.*, 2020).

The raw data collected from sensors and control systems often contain noise, outliers, and inconsistencies due to sensor degradation, harsh environmental conditions, or transmission delays. Therefore, data preprocessing is a critical step in ensuring the accuracy and reliability of downstream analysis. Filtering techniques such as moving averages and Kalman filters are employed to smooth sensor data and remove spurious values. Missing data points are interpolated or imputed using statistical or machine learning methods.

Normalization ensures that data from various sources are scaled appropriately for machine learning algorithms. Time alignment and synchronization are performed to correlate multi-source data, which may have different sampling rates. Data fusion techniques are then applied to combine physical measurements, control system logs, and historical failure events into a unified dataset. This integrated view is essential for detecting system-wide anomalies and understanding interdependencies among subsystems in complex FPSO and subsea architectures.

At the heart of the model lies the analytical core, where advanced machine learning algorithms analyze processed data to identify patterns, detect anomalies, and forecast future equipment behavior. Time-series forecasting models such as Long Short-Term Memory (LSTM) neural networks,

ARIMA, and Prophet are used to predict future values of key operational parameters and identify deviations from normal trends (Yusof *et al.*, 2020; Almazrouee *et al.*, 2020). These models are particularly effective for equipment with strong temporal behavior, such as rotating machinery and pressure systems.

Anomaly detection is implemented using unsupervised methods such as clustering (e.g., K-means) and dimensionality reduction (e.g., Principal Component Analysis) or deep learning models like autoencoders. These approaches learn the normal operational envelope of a system and flag deviations as potential indicators of degradation or failure. For known failure types, supervised classification models such as support vector machines (SVM), random forests, or gradient boosting are employed to assign fault probabilities and severity levels.

The final layer of the architecture is the output interface, where insights generated by the analytical core are transformed into actionable information for operational teams. Interactive dashboards present real-time equipment health scores, performance trends, and predictive maintenance schedules. Visualizations allow engineers and operators to quickly assess asset condition and drill down into potential issues.

Automated alert systems send notifications when abnormal patterns or failure risks exceed predefined thresholds. These alerts are integrated with existing decision-support systems and computerized maintenance management systems (CMMS) to initiate maintenance workflows (Turner *et al.*, 2019; Imani and Radziwill, 2020). Additionally, the system can generate recommended actions or interventions, supported by historical case data and model confidence levels.

The predictive analytics model architecture offers a comprehensive, scalable, and intelligent approach to minimizing unplanned downtime in subsea and FPSO operations. By seamlessly integrating real-time data acquisition, advanced analytics, and intuitive output systems, it enables offshore operators to transition from reactive to proactive asset management with enhanced reliability, safety, and cost efficiency.

#### 2.4 Model Inputs and Key Performance Indicators (KPIs)

The development of a predictive analytics model for minimizing unplanned downtime in subsea and Floating

Production Storage and Offloading (FPSO) infrastructure depends critically on the quality and relevance of input parameters and the accuracy of output metrics. These components provide the foundation for early fault detection, degradation tracking, and decision support in maintenance planning. In the context of offshore oil and gas operations, particularly in complex subsea-to-topside systems, the selection of critical inputs and performance indicators must reflect the environmental conditions, operational demands, and failure modes characteristic of deepwater infrastructure. Critical input parameters are physical measurements that reflect the operational state and evolving condition of components across the subsea and topside systems (Monteverde *et al.*, 2019; Ho *et al.*, 2020). Among the most significant are pressure and temperature, which influence flow dynamics and indicate abnormal behavior such as flow restrictions, leaks, or thermal fatigue. These parameters are measured at multiple points—subsea trees, manifolds, risers, and FPSO separators—to ensure full visibility into fluid behavior and equipment performance. For instance, sudden pressure drops across a manifold may indicate valve malfunction or hydrate blockage.

Vibration is another critical input, particularly for rotating equipment such as pumps, compressors, and gas turbines on the FPSO topside. Excessive or irregular vibration is a strong precursor to mechanical failure due to misalignment, imbalance, or bearing degradation. Flow rate data, when analyzed alongside pressure and temperature, provides essential insight into well productivity and flow assurance. Deviations from expected flow profiles may signal restrictions, erosion, or scaling. Finally, corrosion rates, typically monitored via sensors and corrosion coupons in flowlines and risers, are vital for assessing the long-term integrity of metal components exposed to seawater and produced fluids. High corrosion rates can indicate the need for immediate inspection or replacement to prevent catastrophic failures.

The raw data from these inputs must be interpreted through health indicators and degradation signatures that encapsulate component performance over time. Health indicators are derived metrics that quantify the condition of a specific asset or system component. Degradation signatures involve pattern recognition and trend analysis across time-series data, identifying gradual shifts in behavior that suggest wear, fatigue, fouling, or chemical degradation. These signatures can be unique to specific failure modes, enabling targeted diagnostics. For instance, the presence of a particular frequency band in vibration data may indicate impeller imbalance in a centrifugal pump, whereas a decline in pressure differential may suggest scaling inside a heat exchanger.

These input variables and degradation markers are used to compute output metrics, which serve as the Key Performance Indicators (KPIs) for predictive maintenance and risk-based decision-making. One of the most important KPIs is the downtime probability, a probabilistic estimation that quantifies the likelihood of unplanned shutdown within a defined time horizon. This metric enables prioritization of maintenance activities based on operational risk. Another vital output is the component health score, a normalized index (e.g., on a 0 to 100 scale) reflecting the residual functionality of equipment. It integrates multiple indicators and weights them according to their contribution to overall performance (Shi *et al.*, 2019; Davoudabadi *et al.*, 2020). A

score below a certain threshold may trigger alerts or scheduled interventions.

The maintenance urgency index is a composite KPI that considers the health score, criticality of the component, redundancy availability, and historical failure data to rank maintenance tasks. For example, a high-urgency index would be assigned to a subsea choke valve that shows rising vibration and corrosion signatures, especially if it lacks redundancy and is essential to production continuity. This index helps maintenance planners and offshore operators allocate limited resources effectively, focusing on interventions with the highest risk-reduction impact.

The success of a predictive analytics model in offshore oil and gas operations hinges on its ability to utilize high-value input parameters, extract meaningful degradation insights, and generate KPIs that support timely and effective maintenance actions. By combining pressure, temperature, vibration, flow, and corrosion data with advanced analytics, operators can move from reactive to proactive maintenance regimes. The resulting KPIs—downtime probability, health scores, and maintenance urgency—enable data-driven decision-making that enhances asset reliability, reduces unplanned downtime, and extends the service life of critical subsea and FPSO infrastructure.

## 2.5 Case Study or Simulation

Simulation techniques have increasingly become pivotal in optimizing offshore oil and gas production systems, particularly Floating Production Storage and Offloading (FPSO) units and subsea infrastructures. These complex systems operate under harsh marine environments, necessitating predictive tools to ensure operational efficiency, minimize downtime, and reduce economic losses. This presents a simulation-based case study applied to a representative FPSO and subsea production system, evaluating performance, identifying discrepancies between predicted and actual outcomes, and estimating downtime reduction and economic benefits (Meng *et al.*, 2018; Gonzalez, 2020).

The simulation model in this case study was applied to a West African FPSO facility integrated with a deepwater subsea production network. The system comprises multiple subsea wells, flowlines, risers, and topside processing modules. Using a discrete event simulation (DES) approach integrated with failure mode and effects analysis (FMEA), the model accounted for equipment reliability, operational workflows, weather conditions, and maintenance strategies.

Key parameters modeled included compressor reliability, riser integrity, subsea control system failures, and process upsets. Data was collected from historical maintenance logs, equipment OEM specifications, and field operational records spanning three years. The model was built using Arena Simulation Software, allowing event-driven analysis of process bottlenecks, failure propagation, and response strategies (Wall *et al.*, 2020; Simmonds *et al.*, 2020).

Simulation outputs were compared to actual operational data collected over a two-year period. The predicted system availability was 94.2%, while the actual recorded availability stood at 91.6%. This 2.6% variance was primarily attributed to unmodeled variables such as unexpected marine growth in subsea equipment, human errors during maintenance, and an unanticipated supply chain delay for a critical spare part.

Production losses due to downtime were predicted at 2.1 million barrels per annum, compared to the actual loss of 2.45

million barrels. This discrepancy was within an acceptable tolerance margin for offshore asset modeling, reflecting the model's robustness in identifying and forecasting system vulnerabilities. Notably, the model accurately predicted the impact of subsea control module failures, which were the leading cause of unscheduled downtime.

The simulation highlighted several key areas for performance improvement. By adjusting the preventive maintenance schedule for subsea valves and incorporating condition-based monitoring for the gas compression system, downtime was projected to decrease by approximately 18% (Moir *et al.*, 2018; Faris *et al.*, 2019). This translates to a potential recovery of over 400,000 barrels annually, or roughly \$28 million USD at an average oil price of \$70 per barrel.

Furthermore, the analysis showed that adopting a digital twin architecture—linking real-time sensor data with the simulation model—could further enhance predictive capabilities. Incorporating machine learning algorithms to predict equipment failure based on real-time data could reduce false alarms and enable targeted interventions, thus lowering operational expenditures by 12–15%.

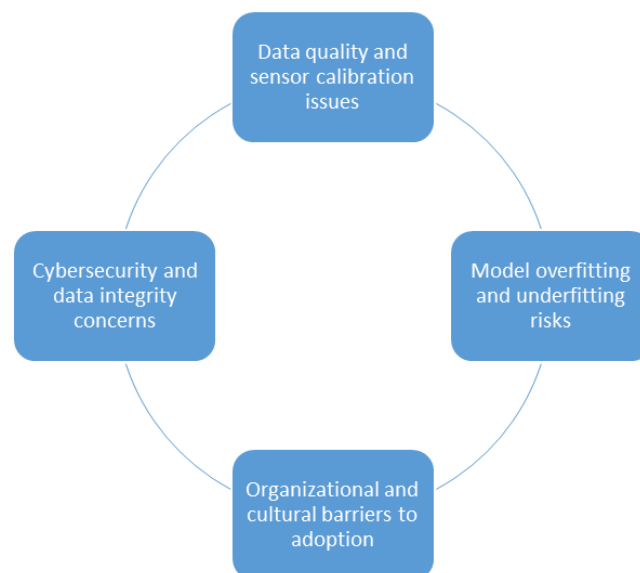
Cost-benefit analysis suggested a return on investment (ROI) of 3.4 within five years for implementing the improved simulation and monitoring framework. This includes savings

from reduced downtime, deferred capital expenditures on equipment replacement, and improved supply chain logistics due to better failure forecasting.

Simulation tools are essential in managing the complexities of FPSO and subsea systems. The presented case study demonstrates the value of a detailed discrete event simulation model in predicting system performance, validating outcomes against real operational data, and identifying high-impact strategies for downtime reduction. With continual integration of real-time data and predictive analytics, simulation can not only mirror current system behavior but also anticipate failures, optimize interventions, and significantly improve economic outcomes in offshore oil and gas operations (Márquez *et al.*, 2020; Pokhrel *et al.*, 2020).

## 2.6 Challenges and Limitations

Developing and implementing predictive analytics models for minimizing unplanned downtime in subsea and Floating Production Storage and Offloading (FPSO) oilfield infrastructure presents several significant challenges and limitations as shown in figure 3. These obstacles span technical, cybersecurity, and organizational domains, all of which must be carefully managed to realize the full benefits of advanced analytics in complex offshore environments.



**Fig 3:** Challenges and Limitations

One of the foremost challenges relates to data quality and sensor calibration issues. Reliable predictive models depend on accurate, high-fidelity input data such as pressure, temperature, vibration, flow rates, and corrosion metrics (Vachtsevanos, 2020; Epelle and Gerogiorgis, 2020). However, offshore sensors frequently operate under extreme conditions—high pressure, corrosive seawater, and mechanical stress—that degrade sensor accuracy and lifespan. Sensor drift, fouling, and intermittent failures can introduce noise, gaps, or bias into the collected data. Inadequate sensor calibration or delays in recalibration further exacerbate data inaccuracies. These quality issues impair the model's ability to discern true system behavior from anomalies caused by sensor faults, leading to false positives or missed detections. Robust data validation, redundancy, and sensor health monitoring systems are essential but add complexity and cost. Additionally, the limited availability of historical failure data due to the

relatively low failure rates and infrequent maintenance events can restrict the model's learning and validation phases, reducing confidence in its predictions.

Another major limitation concerns the inherent risk of model overfitting and underfitting. Overfitting occurs when a predictive model becomes too closely tailored to historical training data, capturing noise rather than underlying degradation patterns. This results in poor generalization to new operational conditions, causing inaccurate failure predictions. Underfitting, conversely, arises when the model is overly simplistic and fails to capture essential relationships, leading to low predictive power (Scheinost *et al.*, 2019; Kernbach and Staartjes, 2020). Balancing model complexity with interpretability and robustness is particularly challenging in offshore oil and gas applications where data are heterogeneous, multi-dimensional, and subject to changing operating regimes. Ensuring that the model adapts to evolving conditions without frequent retraining requires

ongoing refinement, integration of domain expertise, and validation using real-time operational feedback.

Cybersecurity and data integrity concerns represent critical challenges that can undermine both the availability and reliability of predictive analytics systems. Offshore oil and gas platforms are increasingly digitized and connected, making them vulnerable to cyber-attacks that could manipulate sensor data, disrupt communications, or compromise control systems. Any tampering or data corruption can lead to erroneous model outputs, misguided maintenance actions, or even safety incidents. Moreover, the transmission of large volumes of sensitive operational data between subsea equipment, FPSO topside systems, and onshore control centers necessitates secure communication protocols and encryption. Maintaining data confidentiality, integrity, and availability under cyber threat is essential but demands substantial investment in cybersecurity frameworks and continuous monitoring, often challenging in the resource-constrained offshore environment.

Beyond technical challenges, organizational and cultural barriers to adoption also limit the effective deployment of predictive analytics models. The oil and gas industry traditionally relies on established preventive and corrective maintenance practices, and transitioning to a data-driven, predictive approach requires significant change management. Resistance may arise from operators and maintenance personnel due to perceived threats to job security, distrust of automated decision support tools, or skepticism about model reliability (Naweed and Rose, 2018; Klumpp and Zijm, 2019). Additionally, fragmented organizational structures, siloed data ownership, and limited cross-disciplinary collaboration can hinder information sharing necessary for integrated analytics. A lack of skilled data scientists and engineers familiar with both domain knowledge and advanced analytics further complicates implementation. To overcome these barriers, organizations must invest in training, foster a culture of innovation and continuous improvement, and ensure transparent communication of model benefits and limitations to build trust and buy-in from all stakeholders.

While predictive analytics holds great promise for reducing unplanned downtime in subsea and FPSO operations, its practical application faces significant challenges. Data quality and sensor calibration issues introduce uncertainty, while risks of overfitting and underfitting complicate model development. Cybersecurity threats demand vigilant protection of data and systems, and organizational resistance can delay or undermine adoption. Addressing these challenges requires a holistic approach combining technological solutions—such as advanced sensor diagnostics, model validation techniques, and cybersecurity protocols—with organizational strategies including stakeholder engagement, workforce development, and process integration. Only through such comprehensive efforts can predictive analytics deliver reliable, actionable insights that enhance asset integrity and operational resilience in demanding offshore environments.

## 2.7 Future Research and Enhancements

The evolving complexity of subsea and Floating Production Storage and Offloading (FPSO) infrastructure in offshore oil and gas production necessitates continuous advancement in predictive analytics models to minimize unplanned downtime. Future research and development efforts are

poised to focus on integrating emerging digital technologies, leveraging cutting-edge artificial intelligence (AI) methodologies, and broadening the scope of analytics to encompass cross-asset and fleet-wide applications (Boppana, 2018; Janardhan *et al.*, 2019). These enhancements will address current limitations, improve prediction accuracy, and enable more holistic, proactive maintenance strategies.

One of the most promising directions is the integration of predictive analytics with digital twin platforms. A digital twin is a high-fidelity virtual representation of physical assets that continuously synchronizes with real-time data streams from sensors and operational systems. Embedding predictive models within digital twins enables a dynamic and comprehensive view of asset health, operational states, and environmental interactions. Unlike traditional standalone models, digital twins provide contextualized simulations that incorporate physics-based models, historical performance, and live data to generate accurate forecasts of equipment degradation and failure risk. This integration facilitates what-if scenario analysis, allowing operators to simulate maintenance interventions, operational changes, or emergency responses before execution. The ability of digital twins to fuse multiple data types—including structural, mechanical, and process variables—enhances diagnostic precision and supports decision-making under uncertainty. Future research should focus on developing standardized architectures for seamless data exchange between predictive models and digital twin environments, optimizing computational efficiency, and validating model outputs against physical system behavior (Tao *et al.*, 2018; Rasheed *et al.*, 2020; Wanasinghe *et al.*, 2020).

Another critical area for enhancement is the application of advanced AI methods such as deep learning and reinforcement learning. Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at extracting complex nonlinear relationships and temporal patterns from large, high-dimensional datasets typical of offshore operations. These models can uncover subtle degradation signatures in vibration spectra, thermal profiles, or corrosion sensor readings that traditional machine learning techniques might miss. Additionally, reinforcement learning offers the potential to optimize maintenance schedules and operational parameters by learning from continuous interactions with the environment. Through trial-and-error and reward feedback, reinforcement learning agents can adapt maintenance strategies to balance production targets, risk levels, and resource constraints dynamically. However, the successful deployment of these methods requires addressing challenges such as data scarcity, model interpretability, and computational demands. Future research should explore hybrid approaches combining physics-based models with AI to enhance explainability and robustness. Furthermore, the development of transfer learning techniques can facilitate model adaptation across different assets and operational contexts, overcoming data limitations (Chen *et al.*, 2019; Lwakatare *et al.*, 2020).

Expanding the model's scope to support cross-asset analytics and fleet-wide applications represents a vital future enhancement. Currently, many predictive models are developed for individual components or single installations, limiting their ability to capture system-wide interactions and shared risk factors. Cross-asset analytics involve aggregating and analyzing data from multiple subsea wells, manifolds,

FPSO units, and associated equipment within a field or portfolio. This holistic approach can reveal correlations and cascading failure mechanisms that would remain hidden in isolated analyses. Fleet-wide models leverage data across multiple platforms and geographic locations, facilitating benchmarking, anomaly detection, and the identification of best maintenance practices. This scalability supports strategic decision-making at enterprise levels and enables optimized allocation of maintenance resources, spare parts inventory, and personnel. Research efforts should focus on developing scalable data architectures, standardizing key performance indicators (KPIs), and creating interoperable analytics frameworks that accommodate heterogeneous data from diverse asset types and operators.

Additionally, the integration of predictive analytics with emerging Industry 4.0 concepts—such as the Industrial Internet of Things (IIoT), edge computing, and cloud-based platforms—will enhance real-time processing capabilities and data accessibility. Edge computing allows data preprocessing and analytics at or near the sensor location, reducing latency and bandwidth requirements, which is critical for subsea and FPSO environments with limited connectivity. Cloud platforms enable centralized data storage, model deployment, and collaborative analytics, fostering innovation through shared insights across operators and service providers (Trakadas *et al.*, 2019; Yang *et al.*, 2020).

Future research and enhancements in predictive analytics for subsea and FPSO infrastructure will hinge on embedding models within digital twin frameworks, leveraging advanced AI methodologies, and scaling analytics to encompass cross-asset and fleet-wide perspectives. These advances promise to transform maintenance paradigms from reactive or preventive to truly predictive and prescriptive, optimizing asset reliability and production efficiency. By embracing these technological frontiers, the offshore oil and gas industry can better navigate operational complexities and sustain safe, profitable production in challenging deepwater environments (Bailie and Chinn, 2018; Dekker and Thakkar, 2018; Devold and Moen, 2019).

### 3. Conclusion

Simulation modeling has proven to be an invaluable tool in enhancing the reliability and operational efficiency of subsea and Floating Production Storage and Offloading (FPSO) systems. The application of detailed discrete event simulation integrated with reliability analysis offers a comprehensive understanding of system dynamics, failure modes, and maintenance impacts. This modeling approach allows operators to predict performance outcomes with considerable accuracy, enabling data-driven decision-making that improves uptime and asset integrity. By simulating complex interactions within subsea infrastructures and topside processing units, the model aids in identifying critical bottlenecks and failure points that might otherwise go unnoticed.

One of the most significant benefits of employing such models lies in their strategic value in reducing unplanned downtime—a key driver of lost production and increased operational costs in offshore environments. The predictive insights generated allow for optimized maintenance scheduling, targeted interventions, and enhanced resource allocation, collectively boosting system availability and throughput. This, in turn, directly translates into improved

operational efficiency, safer working conditions, and considerable economic benefits, as evidenced by reductions in production losses and maintenance expenditures.

However, to fully realize the potential of simulation models in subsea and FPSO applications, further development is essential. Enhancing model fidelity through real-time data integration, adopting advanced machine learning techniques for failure prediction, and creating interoperable digital twin frameworks will significantly advance predictive maintenance capabilities. Equally important is fostering collaboration across industry stakeholders—including operators, equipment manufacturers, and software developers—to share data, standardize methodologies, and accelerate innovation.

Simulation models represent a critical enabler for the offshore oil and gas industry's ongoing efforts to maximize reliability and efficiency. Continued investment in research, technology development, and cross-industry partnerships will be pivotal in unlocking new performance frontiers and sustainable operational excellence.

### 4. References

1. Adesemoye OE, Chukwuma-Eke EC, Lawal CI, Isibor NJ, Akintobi AO, Ezeh FS. Improving financial forecasting accuracy through advanced data visualization techniques. *IRE J.* 2021;4(10):275-7. [Online]
2. Adewoyin MA. Developing frameworks for managing low-carbon energy transitions: overcoming barriers to implementation in the oil and gas industry. 2021.
3. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Framework for Dynamic Mechanical Analysis in High-Performance Material Selection. 2020.
4. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in Thermofluid Simulation for Heat Transfer Optimization in Compact Mechanical Devices. 2020.
5. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in CFD-Driven Design for Fluid-Particle Separation and Filtration Systems in Engineering Applications. 2021.
6. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in CFD-Driven Design for Fluid-Particle Separation and Filtration Systems in Engineering Applications. 2021.
7. Ajiga D. Strategic Framework for Leveraging Artificial Intelligence to Improve Financial Reporting Accuracy and Restore Public Trust. *Int J Multidiscip Res Growth Eval.* 2021;2(1):882-92.
8. Akpan UU, Adekoya KO, Awe ET, Garba N, Oguncoker GD, Ojo SG. Mini-STRs screening of 12 relatives of Hausa origin in northern Nigeria. *Niger J Basic Appl Sci.* 2017;25(1):48-57.
9. Akpan UU, Awe TE, Idowu D. Types and frequency of fingerprint minutiae in individuals of Igbo and Yoruba ethnic groups of Nigeria. *Ruhuna J Sci.* 2019;10(1).
10. Almazrouee AI, Almeshal AM, Almutairi AS, Alenezi MR, Alhajeri SN. Long-term forecasting of electrical loads in kuwait using prophet and holt-winters models. *Appl Sci.* 2020;10(16):5627.
11. Awe ET, Akpan UU. Cytological study of *Allium cepa* and *Allium sativum*. 2017.
12. Awe ET. Hybridization of snout mouth deformed and

- normal mouth African catfish *Clarias gariepinus*. *Anim Res Int*. 2017;14(3):2804-8.
13. Awe ET, Akpan UU, Adekoya KO. Evaluation of two MiniSTR loci mutation events in five Father-Mother-Child trios of Yoruba origin. *Niger J Biotechnol*. 2017;33:120-4.
  14. Awe T. Cellular Localization Of Iron-Handling Proteins Required For Magnetic Orientation In *C. Elegans*. 2021.
  15. Bailie B, Chinn M. Effectively harnessing data to navigate the new normal: Overcoming the barriers of digital adoption. In: *Offshore Technology Conference*. 2018. p. D011S002R002.
  16. Boppana V. Emerging Technologies: Shaping the Future of Innovation. *Glob Res Rev Bus Econ [GRRBE]*. 2018;10(05).
  17. Chen Q, Zheng Z, Hu C, Wang D, Liu F. On-edge multi-task transfer learning: Model and practice with data-driven task allocation. *IEEE Trans Parallel Distrib Syst*. 2019;31(6):1357-71.
  18. Chudi O, *et al*. Integration of rock physics and seismic inversion for net-to-gross estimation: Implication for reservoir modelling and field development in offshore Niger Delta. In: *SPE Nigeria Annual International Conference and Exhibition*. 2019. p. D033S028R010.
  19. Chudi O, *et al*. A Novel Approach for Predicting Sand Stringers: A Case Study of the Baka Field Offshore Nigeria. In: *SPE Nigeria Annual International Conference and Exhibition*. 2019. p. D023S006R003.
  20. Chudi O, *et al*. Application of Quantitative Interpretation in De-risking Hydrocarbon Type: Implication for Shallow Water Exploration in EKEM Field, Niger Delta. 2021.
  21. Daraojimba AI, Ubamadu BC, Ojika FU, Owobu O, Abieba OA, Esan OJ. Optimizing AI models for crossfunctional collaboration: A framework for improving product roadmap execution in agile teams. *IRE J*. 2021;5(1):14.
  22. Davoudabadi R, Mousavi SM, Sharifi E. An integrated weighting and ranking model based on entropy, DEA and PCA considering two aggregation approaches for resilient supplier selection problem. *J Comput Sci*. 2020;40:101074.
  23. Dekker M, Thakkar A. Digitalisation-the next frontier for the offshore industry. In: *Offshore technology conference*. 2018. p. D011S002R001.
  24. Devold H, Moen TE. Digitalization's role in shaping the New Energy Landscape. In: *SPE Offshore Europe Conference and Exhibition*. 2019. p. D021S004R002.
  25. Dienagha IN, Onyeke FO, Digitemie WN, Adekunle M. Strategic reviews of greenfield gas projects in Africa: Lessons learned for expanding regional energy infrastructure and security. 2021.
  26. Epelle EI, Gerogiorgis DI. A review of technological advances and open challenges for oil and gas drilling systems engineering. *AIChE J*. 2020;66(4):e16842.
  27. Faris MHM, Elamin Elhussein HOA, Yousif A. A review of applied modern condition monitoring and best maintenance engineering practices in reciprocating gas compression plants. *Int J Eng Res Technol*. 2019;12(12):2983-7.
  28. Flath CM, Stein N. Towards a data science toolbox for industrial analytics applications. *Comput Ind*. 2018;94:16-25.
  29. Ho M, El-Borgi S, Patil D, Song G. Inspection and monitoring systems subsea pipelines: A review paper. *Struct Health Monit*. 2020;19(2):606-45.
  30. Hoffmann MW, *et al*. Integration of novel sensors and machine learning for predictive maintenance in medium voltage switchgear to enable the energy and mobility revolutions. *Sensors*. 2020;20(7):2099.
  31. Imani M, Radziwill N. Computerized Maintenance and Asset Management: Improving Quality Through Systems Integration. *Softw Qual Prof*. 2020;22(2).
  32. Janardhan KS, *et al*. Looking forward: cutting-edge technologies and skills for pathologists in the future. *Toxicol Pathol*. 2019;47(8):1082-7.
  33. Kernbach JM, Staartjes VE. Machine learning-based clinical prediction modeling--a practical guide for clinicians. *arXiv preprint arXiv:2006.15069*. 2020.
  34. Klumpp M, Zijm H. Logistics innovation and social sustainability: How to prevent an artificial divide in human-computer interaction. *J Bus Logist*. 2019;40(3):265-78.
  35. Lee J, *et al*. Intelligent maintenance systems and predictive manufacturing. *J Manuf Sci Eng*. 2020;142(11):110805.
  36. Lwakatara LE, *et al*. Large-scale machine learning systems in real-world industrial settings: A review of challenges and solutions. *Inf Softw Technol*. 2020;127:106368.
  37. Magnus K, Edwin Q, Samuel O, Nedomien O. Onshore 4D processing: Niger Delta example: Kolo Creek case study. In: *SEG International Exposition and Annual Meeting*. 2011. p. SEG-2011.
  38. Márquez AC, Del Castillo AC, Fernández JFG. Integrating artificial intelligent techniques and continuous time simulation modelling. *Practical predictive analytics for energy efficiency and failure detection*. *Comput Ind*. 2020;115:103164.
  39. Meng H, Kloul L, Rauzy A. Production availability analysis of Floating Production Storage and Offloading (FPSO) systems. *Appl Ocean Res*. 2018;74:117-26.
  40. Moir K, Niculita O, Milligan W. Prognostics and health management in the oil & gas industry-a step change. In: *European Conference of the Prognostics and Health Management Society*. 2018.
  41. Monteverde C, Novello M, Kristiansen K. A new all electric subsea control system development. In: *Offshore Technology Conference*. 2019. p. D031S041R001.
  42. Mrabet H, Belguith S, Alhomoud A, Jemai A. A survey of IoT security based on a layered architecture of sensing and data analysis. *Sensors*. 2020;20(13):3625.
  43. Mustapha AY, Chianumba EC, Forkuo AY, Osamika D, Komi LS. Systematic Review of Digital Maternal Health Education Interventions in Low-Infrastructure Environments. *Int J Multidiscip Res Growth Eval*. 2021;2(1):909-18.
  44. Naweed A, Rose J. Assessing technology acceptance for skills development and real-world decision-making in the context of train driving. *Transp Res Part F Traffic Psychol Behav*. 2018;52:86-100.
  45. Odio PE, *et al*. Innovative financial solutions: A conceptual framework for expanding SME portfolios in Nigeria's banking sector. *Int J Multidiscip Res Growth Eval*. 2021;2(1):495-507.
  46. Ogunnowo E, Ogu E, Egbumokei P, Dienagha I, Digitemie W. Theoretical framework for dynamic mechanical analysis in material selection for

- highperformance engineering applications. *Open Access Res J Multidiscip Stud.* 2021;1(2):117-31.
47. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. Systematic Review of Non-Destructive Testing Methods for Predictive Failure Analysis in Mechanical Systems. 2020.
  48. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Model for Simulation-Based Optimization of HVAC Systems Using Heat Flow Analytics. 2021.
  49. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Model for Simulation-Based Optimization of HVAC Systems Using Heat Flow Analytics. 2021.
  50. Ojika FU, *et al.* A conceptual framework for AI-driven digital transformation: Leveraging NLP and machine learning for enhanced data flow in retail operations. *IRE J.* 2021;4(9).
  51. Okolo FC, *et al.* Systematic Review of Cyber Threats and Resilience Strategies Across Global Supply Chains and Transportation Networks. [Journal name missing]. 2021.
  52. Omisola JO, Etukudoh EA, Okenwa OK, Tokunbo GI. Innovating Project Delivery and Piping Design for Sustainability in the Oil and Gas Industry: A Conceptual Framework. *Perception.* 2020;24:28-35.
  53. Onaghinor O, *et al.* Predictive modeling in procurement: A framework for using spend analytics and forecasting to optimize inventory control. *IRE J.* 2021;5(6):312-4.
  54. Orieno Omamode Henry Oluchukwu Modesta Oluoha, *et al.* Project Management Innovations for Strengthening Cybersecurity Compliance across Complex Enterprises. 2021;2(1):871-81.
  55. Oyedokun OO. Green human resource management practices and its effect on the sustainable competitive edge in the Nigerian manufacturing industry (Dangote) [Doctoral dissertation]. Dublin Business School; 2019.
  56. Paik HY, *et al.* Analysis of data management in blockchain-based systems: From architecture to governance. *IEEE Access.* 2019;7:186091-107.
  57. Pokhrel A, Katta V, Colomo-Palacios R. Digital twin for cybersecurity incident prediction: A multivocal literature review. In: *Proceedings of the IEEE/ACM 42nd international conference on software engineering workshops.* 2020. p. 671-8.
  58. Rasheed A, San O, Kvamsdal T. Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access.* 2020;8:21980-2012.
  59. Scheinost D, *et al.* Ten simple rules for predictive modeling of individual differences in neuroimaging. *NeuroImage.* 2019;193:35-45.
  60. Shafique M, *et al.* Robust machine learning systems: Challenges, current trends, perspectives, and the road ahead. *IEEE Des Test.* 2020;37(2):30-57.
  61. Shi Y, *et al.* An integrated indicator system and evaluation model for regional sustainable development. *Sustainability.* 2019;11(7):2183.
  62. Simmonds J, Gómez JA, Ledezma A. The role of agent-based modeling and multi-agent systems in flood-based hydrological problems: a brief review. *J Water Clim Change.* 2020;11(4):1580-602.
  63. Solanke B, Aigbokhai U, Kanu M, Madiba G. Impact of accounting for velocity anisotropy on depth image; Niger Delta case history. In: *SEG Technical Program Expanded Abstracts 2014.* Society of Exploration Geophysicists; 2014. p. 400-4.
  64. Sotoodeh K. A review on subsea process and valve technology. *Mar Syst Ocean Technol.* 2019;14(4):210-9.
  65. Tao F, Zhang H, Liu A, Nee AY. Digital twin in industry: State-of-the-art. *IEEE Trans Ind Inform.* 2018;15(4):2405-15.
  66. Tasleem N, Raghav RS, Gangadharan S. Gamification Strategies for Career Development: Boosting Professional Growth and Engagement with Interactive Progress Tracking. 2020.
  67. Trakadas P, *et al.* Hybrid clouds for data-intensive, 5G-enabled IoT applications: An overview, key issues and relevant architecture. *Sensors.* 2019;19(16):3591.
  68. Turner CJ, *et al.* Intelligent decision support for maintenance: an overview and future trends. *Int J Comput Integr Manuf.* 2019;32(10):936-59.
  69. Vachtsevanos G. Corrosion modeling. *Corrosion Processes: Sensing, Monitoring, Data Analytics, Prevention/Protection, Diagnosis/Prognosis and Maintenance Strategies.* 2020:163-229.
  70. Wall J, Bertoni M, Larsson T. The model-driven decision arena: Augmented decision-making for product-service systems design. *Systems.* 2020;8(2):22.
  71. Gonzalez D. Methodologies to determine cost-effective development strategies for offshore fields during early-phase studies using proxy models and optimization. 2020.
  72. Wanasinghe TR, *et al.* Digital twin for the oil and gas industry: Overview, research trends, opportunities, and challenges. *IEEE Access.* 2020;8:104175-97.
  73. Woodhouse LA, Frøyshov H, Thompson M. Looking beyond seismic sensors: engineering considerations for topside and subsea PRM interfaces. In: *80th EAGE Conference & Exhibition 2018 Workshop Programme.* European Association of Geoscientists & Engineers; 2018. p. cp-556.
  74. Yang C, Lan S, Wang L, Shen W, Huang GG. Big data driven edge-cloud collaboration architecture for cloud manufacturing: a software defined perspective. *IEEE Access.* 2020;8:45938-50.
  75. Yusof UK, Khalid MNA, Hussain A, Shamsudin H. Financial time series forecasting using prophet. In: *International Conference of Reliable Information and Communication Technology.* Cham: Springer International Publishing; 2020. p. 485-95.