© MAR 2020 | IRE Journals | Volume 3 Issue 9 | ISSN: 2456-8880

Integrating Machine Learning into Digital Twin Frameworks for Predictive Surveillance and Automated Recovery of Deepwater Subsea Assets

MALVERN IHEANYICHUKWU ODUM[1], IDUATE DIGITEMIE JASON[2], DAZOK DONALD JAMBOL[3]
[1]Shell Nigeria Exploration and Production Company (SNEPCo), Nigeria
[2]Independent Researcher, Nigeria
[3]Shell Petroleum Development Company of Nigeria Ltd, Nigeria

Abstract- The increasing complexity and inaccessibility of deepwater subsea environments demand advanced, intelligent solutions for asset monitoring, fault prediction, and recovery. This paper explores the integration of machine learning into digital twin frameworks as a transformative approach for predictive surveillance and automated recovery of subsea infrastructure. By combining real-time data acquisition with intelligent algorithms, digital twins evolve from passive representations into proactive, decision-making systems capable of early anomaly detection, failure trajectory modeling, and autonomous intervention. The study examines key components of this integration, including data preprocessing, feature engineering, online model updating, and reinforcement learning-based decision support systems. It also discusses the development of cyber-physical feedback loops that enable actuation through remotely operated or autonomous vehicles in response to model-driven insights. The integration enhances adaptability, operational continuity, and system resilience, significantly reducing downtime and improving safety in remote offshore operations. This work underscores the potential of machine learning to redefine the role of digital twins in subsea engineering, paving the way for more autonomous, intelligent, and cost-effective asset management in extreme underwater conditions.

Indexed Terms- Digital Twin, Machine Learning, Predictive Surveillance, Subsea Asset Management, Autonomous Recovery, Reinforcement Learning

I. INTRODUCTION

1.1 Background Context

Deepwater subsea assets form the backbone of offshore oil and gas operations, enabling the extraction, processing, and transportation of hydrocarbons from seabeds located hundreds or even thousands of meters below the ocean surface [1, 2]. These assets include subsea trees, manifolds, pipelines, control systems, and critical infrastructures operating in one of the most extreme and inaccessible environments on Earth [3, 4]. Given their remoteness, failures in these systems often result in substantial economic losses and environmental risks [5, 6]. Traditionally, the health of such assets has been monitored through periodic inspections and reactive maintenance, a model that lacks the speed and precision required for modern deepwater operations [7, 8].

In recent years, digital twin technology has emerged as a game-changer for industrial asset management. A digital twin is a dynamic, real-time digital replica of a physical system, fed by data from sensors and operational inputs. In subsea applications, it enables operators to visualize asset behavior, simulate performance under various conditions, and identify early signs of degradation [9]. By creating a continuously updated digital representation of subsea assets, this technology allows for more accurate diagnostics and lifecycle predictions, enhancing reliability and operational decision-making. As offshore infrastructure ages and becomes more complex, the relevance of digital twins in maintaining asset integrity continues to grow rapidly [10].

1.2 Motivation for Integration

Operating and maintaining deepwater subsea assets present unique challenges that are often absent in onshore or shallow-water settings. These include high hydrostatic pressure, corrosive seawater, poor accessibility, and severe limitations in data transmission and power supply [4, 11]. Physical inspections via remotely operated vehicles are costly and time-intensive, while environmental risks such as undetected leaks or mechanical failure can be catastrophic. Moreover, real-time fault detection remains elusive due to latency in communication and data interpretation. These obstacles severely constrain the effectiveness of traditional maintenance strategies, which tend to be reactive rather than proactive [12, 13].

This context highlights the urgent need for intelligent, autonomous systems capable of interpreting complex data patterns, identifying anomalies, and making decisions without human intervention. Machine learning (ML), with its capacity for pattern recognition, predictive modeling, and continuous learning, is well-suited to address this need [14]. Integrating ML into digital twins allows for real-time surveillance that not only identifies but also anticipates system failures based on subtle changes in operational behavior. Furthermore, ML enables continuous adaptation to evolving conditions, such as shifting sediment patterns or mechanical wear, making surveillance systems more resilient over time [15, 16].

The integration is not just a matter of technological convenience; it represents a strategic shift toward autonomy in subsea asset management. As the industry moves toward uncrewed operations and remote-control centers, embedding ML within digital twin frameworks becomes crucial for achieving efficiency, safety, and sustainability.

1.3 Research Objective

This paper aims to investigate the integration of ML algorithms within digital twin frameworks specifically tailored for deepwater subsea applications. The focus is on enhancing predictive surveillance, the ability to detect and anticipate asset failures before they escalate, and on enabling automated recovery mechanisms that can respond swiftly to emergent faults. The core objective is to establish how data-driven intelligence can transform digital twins from passive monitoring tools into proactive, decision-making systems capable of executing or recommending recovery actions with minimal human input.

The research emphasizes algorithmic adaptability, robustness in extreme conditions, and the need for closed-loop control systems that link virtual models with physical responses. By doing so, the study provides insights into how predictive models trained on historical and real-time data can uncover hidden failure patterns, even in datasets characterized by noise, sparsity, or irregular sampling, a common issue in underwater environments. Additionally, it explores how ML models can interface with actuators and recovery systems to form a responsive digital ecosystem.

Ultimately, the objective is to highlight the transformative potential of integrating ML into digital twin ecosystems, not only to improve operational reliability and reduce downtime, but also to pave the way for semi-autonomous or fully autonomous subsea systems capable of managing their own health in real time.

II. FOUNDATIONS OF DIGITAL TWIN TECHNOLOGY IN SUBSEA SYSTEMS

2.1 Digital Twin Architecture for Subsea Environments

The architecture of a digital twin designed for deepwater applications must account for the extreme physical and operational conditions characteristic of subsea environments [17]. At its core, a digital twin consists of three primary components: the physical asset, the virtual representation, and the data flow that connects them [18, 19]. The physical asset, such as a subsea wellhead or flowline, operates under high pressure and low temperature, often buried under sediment or installed in hard-to-reach locations [20]. Capturing the condition and performance of these assets in real time requires a robust network of sensors, including those for pressure, vibration, temperature, and acoustic signals [21, 22].

The virtual component, typically hosted in onshore or cloud-based environments, mirrors the state of the asset using dynamic modeling techniques. These models are not static blueprints but live systems that incorporate historical performance, current readings, and expected future behavior. The fidelity of this virtual twin depends heavily on how accurately it can simulate complex fluid dynamics, mechanical stresses, and chemical interactions within the subsea asset [23, 24].

Critical to this system is the data flow layer, which ensures that collected information is processed and transmitted effectively. In deepwater applications, this involves overcoming limited communication infrastructure and ensuring the security and reliability of data transfer. The system must be designed to handle intermittent connectivity and leverage edge computing where possible to reduce latency [25, 26].

2.2 Data Acquisition and Communication Challenges

Data acquisition from subsea systems presents a unique set of obstacles not encountered in surface or land-based environments. The first major challenge lies in the limited accessibility of assets [27, 28]. Sensors deployed must be extremely resilient, able to function reliably under extreme hydrostatic pressures, often exceeding 10,000 psi, and temperatures that fluctuate with ocean currents. This harsh setting limits the variety and placement of sensing devices, which in turn restricts the volume and resolution of available data [29, 30].

Secondly, the signal transmission medium is constrained by the physical properties of seawater. Wireless signals such as radio frequencies degrade rapidly underwater, pushing operators to rely on acoustics or fiber-optic connections [31, 32]. Acoustic telemetry, while useful, suffers from low bandwidth and high latency, making real-time communication difficult. Fiber optics provide higher fidelity but come with significant installation and maintenance costs. These limitations often result in intermittent data streams with noisy or incomplete datasets [33, 34].

Additionally, the presence of marine growth, sediment buildup, and equipment wear can degrade sensor performance over time, leading to errors or drift in readings[35, 36]. As a result, digital twins must incorporate robust filtering algorithms and anomaly detection systems to ensure that faulty data does not compromise system integrity. The architecture must also support data compression, validation, and local pre-processing to minimize the burden on transmission links [37, 38].

2.3 Lifecycle Management of Digital Twins

Digital twins are not one-time constructs but evolving entities that must be managed over the full lifecycle of a subsea asset, from concept and design through deployment, operation, maintenance, and ultimately, decommissioning [39, 40]. At the design phase, digital twins assist in simulating performance scenarios, stress-testing materials, and optimizing configurations before physical construction. These simulations help reduce design flaws and ensure better asset reliability once deployed [41, 42].

As the asset enters its operational phase, the digital twin transitions into a real-time monitoring and decision-support tool. The models must be continuously calibrated against real-world data to reflect the actual condition of the asset [43]. This is especially important in deepwater environments where direct inspections are infrequent, and reliance on virtual diagnostics is high. Predictive algorithms are incorporated to project wear patterns, corrosion rates, or fatigue cycles based on operating history and environmental conditions [44, 45].

Over time, asset behavior may diverge from its original design assumptions due to cumulative wear, system modifications, or unanticipated interactions. Digital twins must adapt accordingly, updating their models, learning from new data, and discarding outdated baselines [45, 46]. Lifecycle management, therefore, is not merely a maintenance task but a knowledge-driven evolution. During decommissioning, the digital twin provides critical insights into the safest and most cost-effective disassembly methods, leveraging historical performance data and environmental models [47, 48].

III. ROLE OF MACHINE LEARNING IN PREDICTIVE SURVEILLANCE

3.1 ML Techniques for Anomaly Detection

Anomaly detection is central to predictive surveillance in subsea environments, where unanticipated failures can lead to costly downtime or environmental disasters. ML offers robust methods to detect subtle deviations in system behavior that may precede critical events [49, 50]. Supervised learning techniques, such as support vector machines and deep neural networks, can classify operational states and identify known failure patterns, provided sufficient labeled historical data exists. These models learn from annotated datasets where normal and faulty states are explicitly defined, enabling accurate prediction when similar patterns recur [51, 52].

However, in deepwater applications, labeled failure data is often scarce due to the high reliability expectations and limited occurrence of events. In such cases, unsupervised techniques become vital. Algorithms such as k-means clustering, isolation forests, or autoencoders can model "normal" behavior based on unlabelled operational data [53, 54]. Anomalies are then identified as outliers, instances that deviate significantly from these learned patterns. These methods are particularly useful when dealing with high-dimensional sensor data with complex interdependencies [55, 56].

In both approaches, anomaly scores or confidence metrics are generated to quantify risk levels [57, 58]. These scores can be embedded into dashboards or decision-support systems to trigger alerts, initiate diagnostics, or feed into automated recovery protocols. ML's adaptability makes it uniquely capable of navigating the unpredictable and noisy nature of subsea environments [59, 60].

3.2 Data Preprocessing and Feature Engineering

Raw data obtained from subsea sensors is typically unstructured, noisy, and irregular due to challenging operating conditions and communication constraints. Effective ML implementation begins with rigorous data preprocessing to ensure the reliability of downstream analytics. This phase includes the removal of corrupt entries, outliers, and duplicated readings [61, 62]. Missing values are handled through interpolation, imputation, or signal reconstruction techniques, depending on the severity and context of the gaps. Signal denoising, often using filters like Kalman or wavelet transforms, is crucial for mitigating interference from ambient oceanic noise or mechanical vibrations [63-65].

Normalization follows, allowing the model to treat input variables with vastly different scales, such as pressure (measured in thousands of psi) and temperature (in degrees Celsius), uniformly. Techniques such as min-max scaling or z-score standardization help align data for more stable learning behavior. Once cleaned and normalized, the next challenge is feature extraction. This involves identifying and engineering variables that provide meaningful representations of the system's physical behavior. Derived features may include vibration frequency trends, pressure gradients, or flow rate deviations over time [66, 67].

Feature engineering is particularly impactful in time-series models, where lagged variables, rolling statistics, and domain-specific thresholds help uncover relationships otherwise hidden in raw data. The quality of these features significantly influences model accuracy, especially in complex systems like deepwater infrastructure with nonlinear dynamics [68-70].

3.3 Real-Time Analytics and Model Updating

Real-time surveillance in subsea systems demands more than static models; it requires adaptive learning frameworks that evolve with operational data. Online learning addresses this need by updating model parameters incrementally as new data streams in, without the need to retrain the model from scratch [71, 72]. This is particularly beneficial in dynamic environments where operating conditions change due to external forces like shifting seabed topology, marine life interference, or gradual component wear. Online algorithms, such as stochastic gradient descent-based classifiers or adaptive boosting methods, allow digital twins to remain current and context-aware [73, 74].

To sustain high performance, models must be continuously validated against ground truth events or expert input. Drift detection techniques are employed to monitor when a model's predictions begin to deviate from actual outcomes, indicating a need for recalibration. Ensemble methods can also be utilized, combining predictions from multiple models to improve robustness and reduce the impact of noise or rare anomalies [75, 76].

Edge computing infrastructure is often leveraged in this context, enabling localized analytics on subsea control modules or surface buoys before transmitting summaries to onshore servers. This reduces latency and ensures faster responses to emerging threats. Real-time model updating transforms digital twins from passive monitors into intelligent agents, capable of proactive decision-making in complex underwater environments [77, 78].

IV. INTELLIGENT RECOVERY AND AUTONOMOUS DECISION-MAKING

4.1 Predictive Maintenance vs. Automated Recovery

Predictive maintenance and automated recovery represent two distinct paradigms in subsea asset management, each with different operational implications. Predictive maintenance is rooted in foresight; it uses condition-monitoring data and historical trends to forecast when a component is likely to fail, enabling operators to schedule inspections or replacements just before failure occurs [79, 80]. This approach minimizes unnecessary interventions while extending asset life. However, it still relies heavily on human judgment and planning, particularly in interpreting model outputs and coordinating physical interventions, often requiring downtime or ROV deployment [81-83].

In contrast, automated recovery extends the concept further by not only predicting failures but also initiating predefined or adaptive corrective actions without human input [84, 85]. ML plays a crucial role here, particularly in failure trajectory prediction, where algorithms map potential degradation paths and assess cascading impacts across interconnected components. These models simulate multiple scenarios to identify the most probable sequence of events following an anomaly, allowing the system to prepare or initiate immediate responses [86, 87].

Automated recovery is especially critical in time-sensitive or remote subsea settings where manual intervention is delayed or impractical. By transitioning from diagnostics to action, ML-driven recovery frameworks significantly reduce response time and increase system resilience, making them a logical progression beyond conventional predictive maintenance models [88-90].

4.2 Decision Support Systems with Reinforcement Learning

Reinforcement learning (RL) introduces a paradigm shift in how decisions are made within digital twin environments. Unlike traditional supervised learning, which relies on static datasets, RL enables systems to learn optimal actions through interaction with their environment. In subsea applications, RL agents can be trained to select recovery actions based on continuous feedback from the digital twin, improving performance over time through trial-and-error simulation. This is particularly valuable in complex systems where predefined rule-based responses may not cover all operational edge cases [91, 92].

For instance, an RL agent monitoring pressure anomalies in a subsea pipeline might learn that reducing flow rates gradually, rather than triggering an immediate shutdown, leads to better long-term outcomes in similar past scenarios [93, 94]. Such agents operate within a reward framework, where actions leading to asset stability and safety are positively reinforced, while those resulting in degradation or inefficiency are penalized. Over time, these agents develop policies that generalize across multiple failure modes and operational conditions [95-97].

Integrating RL into decision support systems augments the autonomy of digital twins by equipping them with strategic planning capabilities. Operators are then presented with data-driven recommendations that consider not just immediate fixes, but long-term system health and efficiency. This reduces human cognitive load and enhances consistency in high-stakes decision-making [98, 99].

4.3 Cyber-Physical Integration and Actuation Feedback Loops

The final step in achieving autonomous recovery lies in the seamless integration between the digital twin and the physical system, forming a cyber-physical loop. In this architecture, ML models not only monitor and diagnose asset behavior but also drive actuation commands through control interfaces [100, 101]. These commands are transmitted to intervention mechanisms such as remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs), or embedded actuation systems that adjust valves, reroute flows, or engage emergency protocols in real time [102, 103].

A critical advantage of this feedback loop is its ability to execute corrective actions without waiting for surface-based instructions, thereby reducing latency and improving responsiveness [104, 105]. For example, if an anomaly is detected in a wellhead's pressure regulation system, the digital twin, using pre-trained models, can assess the severity and autonomously direct a nearby AUV to inspect or adjust the valve settings. Such interactions require a tightly coupled interface between virtual analytics and hardware-level execution [106-108].

Reliability in this integration depends on model interpretability, actuator precision, and secure communication channels. Furthermore, sensor feedback post-actuation is reintegrated into the twin, closing the loop and enabling the system to evaluate its own performance. This dynamic interaction marks the transition from digital monitoring systems to intelligent, responsive subsea agents [109-111].

CONCLUSION

This paper has examined the transformative role of machine learning in enhancing the functionality and utility of digital twin frameworks for deepwater subsea asset management. By integrating intelligent algorithms into these virtual replicas, digital twins evolve from static monitoring platforms into dynamic systems capable of autonomous surveillance, fault detection, and recovery planning. ML enhances the twins' ability to interpret noisy and incomplete subsea data, detect early signs of degradation, and make predictive assessments that inform real-time interventions. Furthermore, adaptive models ensure that digital twins remain responsive to evolving asset conditions, enabling a continuous alignment between virtual predictions and physical realities.

The discussion highlighted the importance of robust data preprocessing, time-series feature engineering, and model updating in ensuring accurate and timely predictions. It also explored advanced techniques such as reinforcement learning and cyber-physical actuation loops, which position digital twins as not just mirrors of operational systems but as intelligent agents capable of initiating action. In doing so, the paper underscores how this integration improves the reliability, safety, and longevity of critical infrastructure in extreme underwater environments. The fusion of ML with digital twin architecture sets a new standard for autonomous asset management in subsea domains.

While significant strides have been made, several research directions remain open for exploration. One promising area is the development of hybrid AI systems that combine data-driven machine learning with physics-based simulation models. These hybrid models could enhance predictive accuracy by grounding data interpretations in the fundamental physical behaviors of subsea systems, particularly in scenarios where sensor data is sparse or ambiguous. Another avenue involves the creation of long-term self-adaptive digital twins capable of learning not just from operational data but also from changes in system topology, component upgrades, or environmental shifts.

There is also growing interest in lightweight, energy-efficient algorithms that can run on edge devices embedded within subsea control modules. These would enable decentralized decision-making, reducing dependency on high-bandwidth data transmission to surface platforms. Additionally, further research is needed on explainable AI methods that can clarify how complex models arrive at specific predictions, an essential feature for risk-critical domains like subsea operations. Finally, regulatory frameworks and cybersecurity protocols must evolve alongside technical advancements to ensure that intelligent subsea systems remain secure, transparent, and trustworthy. Interdisciplinary collaboration will be essential in addressing these challenges and unlocking the full potential of intelligent digital twins in subsea environments.

REFERENCES

[1] K. Narula and K. Narula, "Oceans as a source of hydrocarbon energy," *The Maritime Dimension of Sustainable Energy Security,* pp. 145-162, 2019.

[2] P. Harris *et al.*, "Offshore hydrocarbon industries," *The First Global Integrated Marine Assessment. United Nations, New York,* 2016.

[3] J. A. Skinner, *Russian capacity to develop its offshore hydrocarbon resources in the Kara Sea: Arctic and global implications*. University of Alaska Fairbanks, 2016.

[4] C. Mudrak, "Subsea production systems-A review of components, maintenance and reliability," 2016.

[5] M. Kashubsky, *Offshore Oil and Gas Installations Security: An International Perspective*. Informa Law from Routledge, 2015.

[6] T. T. Williams, J. Pappas, and K. Perry, "Ultra-Deepwater and Unconventional Natural Gas and Other Petroleum Resources Program Administration," Research Partnership to Secure Energy for America, Houston, TX (United States), 2016.

[7] H. Htike Aung, "Deep sea mining–what makes it different to offshore oil and gas applications?," 2015.

[8] J. G. Speight, *Handbook of offshore oil and gas operations*. Elsevier, 2014.

[9] M. H. Patel, *Dynamics of offshore structures*. Butterworth-Heinemann, 2013.

[10] N. Mqadi, "Application of IoT (Internet of Things) in the monitoring and control of offshore oil & gas production platforms," 2020.

[11] P. B. Kondapi, Y. D. Chin, A. Srivastava, and Z. F. Yang, "How will subsea processing and pumping technologies enable future deepwater field developments?," in *Offshore technology conference*, 2017: OTC, p. D031S033R001.

[12] M. Maddahi and S. J. Mortazavi, "A review on offshore concepts and feasbility study considerations," in *SPE Asia Pacific Oil and Gas Conference and Exhibition*, 2011: SPE, pp. SPE-147875-MS.

[13] S. L. Scott, D. Devegowda, and A. M. Martin, "Assessment of subsea production & well systems," *Department of Petroleum Engineering, Texas A&M University, Final Report Submitted to the US Department of Interior–Minerals Management Service (MMS), Technology Assessment & Research (TA&R) Program,* 2004.

[14] J. M. Pappas and D. Richardson, "Overview of Subsea Monitoring and Inspection Technologies Development in RPSEA," in *Offshore Technology Conference*, 2012: OTC, pp. OTC-23183-MS.

[15] M. Shafiee, T. Elusakin, and E. Enjema, "Subsea blowout preventer (BOP): Design, reliability, testing, deployment, and operation and maintenance challenges," *Journal of Loss Prevention in the Process Industries,* vol. 66, p. 104170, 2020.

[16] L. Penati, M. Ducceschi, A. Favi, and D. Rossin, "Installation Challenges for Ultra-Deep Waters," in *Offshore Mediterranean Conference and Exhibition*, 2015: OMC, pp. OMC-2015-441.

[17] B. Pan and W. Cui, *Multidisciplinary design optimization and its application in deep manned submersible design*. Springer, 2020.

[18] M. Ho, S. El-Borgi, D. Patil, and G. Song, "Inspection and monitoring systems subsea pipelines: A review paper," *Structural Health Monitoring,* vol. 19, no. 2, pp. 606-645, 2020.

[19] J. D. Gage and P. A. Tyler, *Deep-sea biology: a natural history of organisms at the deep-sea floor*. Cambridge University Press, 1991.

[20] J. O. Omisola, J. O. Shiyanbola, and G. O. Osho, "A Systems-Based Framework for ISO 9000 Compliance: Applying Statistical Quality Control and Continuous Improvement Tools in US Manufacturing," *Unknown Journal,* 2020.

[21] J. H. Johansen, "Non-linear control and digital twin modeling of the REMUS 100 AUV," NTNU, 2020.

[22] M. B. LeBlanc, "Digital twin technology for enhanced upstream capability in oil and gas," Massachusetts Institute of Technology, 2020.

[23] M. Fox, *Interactive architecture: adaptive world*. Chronicle Books, 2016.

[24] B. H. Bratton, *The stack: On software and sovereignty*. MIT press, 2016.

[25] A.-L. Vion, "Software asset management and cloud computing," Université Grenoble Alpes, 2018.

[26] M. H. Syed, "Modeling and Security in Cloud and Related Ecosystems," Florida Atlantic University, 2019.

[27] B. Basson, "The right to privacy: how the proposed POPI Bill will impact data security in a Cloud Computing environment," Stellenbosch: Stellenbosch University, 2014.

[28] M. A. Shalan, "Risk and Governance Considerations in Cloud Era," in *Handbook of Research on End-to-End Cloud Computing Architecture Design*: IGI Global, 2017, pp. 376-409.

[29] C. Roberts, "Cloud, Risk and Security," ed: Sep.

[30] D. Galar, U. Kumar, and D. Seneviratne, *Robots, drones, UAVs and UGVs for operation and maintenance*. CRC Press, 2020.

[31] S. O. Muhanji, A. E. Flint, and A. M. Farid, *eIoT: The development of the energy internet of things in energy infrastructure*. Springer Nature, 2019.

[32] L. Huang, "BIM-based scheduling for precast assembly and tower crane lifting," 2020.

[33] D. E. Bakken, A. Bose, C. H. Hauser, D. E. Whitehead, and G. C. Zweigle, "Smart generation and transmission with coherent, real-time data," *Proceedings of the IEEE,* vol. 99, no. 6, pp. 928-951, 2011.

[34] V. W. Chan, K. L. Hall, E. Modiano, and K. A. Rauschenbach, "Architectures and technologies for high-speed optical data networks," *Journal of lightwave Technology,* vol. 16, no. 12, p. 2146, 1998.

[35] B. M. Howe *et al.*, "SMART cables for observing the global ocean: science and implementation," *Frontiers in Marine Science,* vol. 6, p. 424, 2019.

[36] P. G. E. Lumens, "Fibre-optic sensing for application in oil and gas wells," 2014.

[37] Z. Ma, M. Xiao, Y. Xiao, Z. Pang, H. V. Poor, and B. Vucetic, "High-reliability and low-latency wireless communication for internet of things: Challenges, fundamentals, and enabling technologies," *IEEE Internet of Things Journal,* vol. 6, no. 5, pp. 7946-7970, 2019.

[38] S. Z. Kamal, "Fiber optic sensing: Evolution to value," in *SPE Intelligent Energy International Conference and Exhibition*, 2014: SPE, pp. SPE-167907-MS.

[39] P. Cawley, "Structural health monitoring: Closing the gap between research and industrial deployment," *Structural health monitoring,* vol. 17, no. 5, pp. 1225-1244, 2018.

[40] H. Jamali-Rad and X. Campman, "Internet of Things-based wireless networking for seismic applications," *Geophysical Prospecting,* vol. 66, no. 4, pp. 833-853, 2018.

[41] G. Stone, "Condition monitoring and diagnostics of motor and stator windings–A review," *IEEE Transactions on Dielectrics and Electrical Insulation,* vol. 20, no. 6, pp. 2073-2080, 2013.

[42] A. V. Gribok, "Performance of Advanced Signal Processing and Pattern Recognition Algorithms Using Raw Data from Ultrasonic Guided Waves and Fiber Optics Transducers," Idaho National Lab.(INL), Idaho Falls, ID (United States), 2018.

[43] D. Wagg, K. Worden, R. Barthorpe, and P. Gardner, "Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering,* vol. 6, no. 3, p. 030901, 2020.

[44] A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers," *arXiv preprint arXiv:1910.01719,* 2019.

[45] A. Rasheed, O. San, and T. Kvamsdal, "Digital twin: Values, challenges and enablers from a

modeling perspective," *IEEE access,* vol. 8, pp. 21980-22012, 2020.

[46] A. Diez-Olivan, J. Del Ser, D. Galar, and B. Sierra, "Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0," *Information Fusion,* vol. 50, pp. 92-111, 2019.

[47] J. Bickford, D. L. Van Bossuyt, P. Beery, and A. Pollman, "Operationalizing digital twins through model-based systems engineering methods," *Systems Engineering,* vol. 23, no. 6, pp. 724-750, 2020.

[48] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," *Transdisciplinary perspectives on complex systems: New findings and approaches,* pp. 85-113, 2017.

[49] S. S. Johansen, "On developing a digital twin for fault detection in drivetrains of offshore wind turbines," NTNU, 2018.

[50] J. Lee, J. Ni, J. Singh, B. Jiang, M. Azamfar, and J. Feng, "Intelligent maintenance systems and predictive manufacturing," *Journal of Manufacturing Science and Engineering,* vol. 142, no. 11, p. 110805, 2020.

[51] K. Gorkovenko, D. J. Burnett, J. K. Thorp, D. Richards, and D. Murray-Rust, "Exploring the future of data-driven product design," in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1-14.

[52] C. E. Dibsdale, *Aerospace Predictive Maintenance*. SAE International, 2020.

[53] R. Moura, M. Beer, E. Patelli, J. Lewis, and F. Knoll, "Learning from accidents: Interactions between human factors, technology and organisations as a central element to validate risk studies," *Safety Science,* vol. 99, pp. 196-214, 2017.

[54] A. Singh, S. Sankaran, S. Ambre, R. Srikonda, and Z. Houston, "Improving Deepwater Facility Uptime Using Machine Learning Approach," in *SPE Annual Technical Conference and Exhibition?*, 2019: SPE, p. D021S020R004.

[55] P. Jiang, M. Maghrebi, A. Crosky, and S. Saydam, "Unsupervised deep learning for data-driven reliability and risk analysis of engineered systems," in *Handbook of neural computation*: Elsevier, 2017, pp. 417-431.

[56] Y. Chang *et al.*, "A Bayesian Network model for risk analysis of deepwater drilling riser fracture failure," *Ocean Engineering,* vol. 181, pp. 1-12, 2019.

[57] C. Castillo, *Big crisis data: social media in disasters and time-critical situations*. Cambridge University Press, 2016.

[58] K. R. Holdaway, *Harness oil and gas big data with analytics: Optimize exploration and production with data-driven models*. John Wiley & Sons, 2014.

[59] M. Diesing, S. L. Green, D. Stephens, R. M. Lark, H. A. Stewart, and D. Dove, "Mapping seabed sediments: Comparison of manual, geostatistical, object-based image analysis and machine learning approaches," *Continental Shelf Research,* vol. 84, pp. 107-119, 2014.

[60] B. Cai, Y. Liu, Z. Liu, Y. Chang, and L. Jiang, *Bayesian networks for reliability engineering*. Springer, 2020.

[61] T. Orekan and P. Zhang, *Underwater wireless power transfer: smart ocean energy converters*. Springer, 2019.

[62] M. C. Kerman, W. Jiang, A. F. Blumberg, and S. E. Buttrey, "Event detection challenges, methods, and applications in natural and artificial systems," 2009.

[63] B. Qian *et al.*, "Orchestrating the development lifecycle of machine learning-based IoT applications: A taxonomy and survey," *ACM Computing Surveys (CSUR),* vol. 53, no. 4, pp. 1-47, 2020.

[64] P. Goel, P. Jain, H. J. Pasman, E. Pistikopoulos, and A. Datta, "Integration of data analytics with cloud services for safer process systems, application examples and implementation challenges," *Journal of Loss Prevention in the Process Industries,* vol. 68, p. 104316, 2020.

[65] F. Majdani Shabestari, "Automated anomaly recognition in real time data streams for oil and gas industry," 2020.

[66] A. A. Abayomi, J. C. Ogeawuchi, A. Y. Onifade, and O. Aderemi, "Systematic Review of Marketing Attribution Techniques for Omnichannel Customer Acquisition Models."

[67] E. O. OGUNNOWO, M. A. ADEWOYIN, J. E. FIEMOTONGHA, T. O. IGUNMA, and A. K. ADELEKE, "Systematic Review of Non-Destructive Testing Methods for Predictive Failure Analysis in Mechanical Systems," 2020.

[68] O. O. Ajayi, N. Chukwurah, and A. S. Adebayo, "Securing 5G Network Infrastructure From Protocol-Based Attacks and Network Slicing Exploits in Advanced Telecommunications."

[69] O.-E. E. Akpe, B. C. Ubanadu, A. I. Daraojimba, O. A. Agboola, and E. Ogbuefi, "A Strategic Framework for Aligning Fulfillment Speed, Customer Satisfaction, and Warehouse Team Efficiency."

[70] J. O. Omisola, E. A. Etukudoh, E. C. Onukwulu, and G. O. Osho, "Sustainability and Efficiency in Global Supply Chain Operations Using Data-Driven Strategies and Advanced Business Analytics."

[71] A. Y. Onifade, R. E. Dosumu, A. A. Abayomi, and O. Aderemi, "Advances in Cross-Industry Application of Predictive Marketing Intelligence for Revenue Uplift."

[72] G. Omoegun, J. E. Fiemotongha, J. O. Omisola, O. K. Okenwa, and O. Onaghinor, "Advances in ERP-Integrated Logistics Management for Reducing Delivery Delays and Enhancing Project Delivery."

[73] G. P. Ifenatuora, O. Awoyemi, and F. A. Atobatele, "Advances in Accessible and Culturally Relevant eLearning Strategies for US Corporate and Government Workforce Training."

[74] A. Y. Onifade, J. C. Ogeawuchi, A. A. Abayomi, and O. Aderemi, "Advances in CRM-Driven Marketing Intelligence for Enhancing Conversion Rates and Lifetime Value Models."

[75] G. P. Ifenatuora, O. Awoyemi, and F. A. Atobatele, "Advances in Instructional Design for Experiential Mobile Classrooms in Resource-Constrained Environments."

[76] E. C. Chianumba, A. Y. Forkuo, A. Y. Mustapha, D. Osamika, and L. S. Komi, "Advances in Preventive Care Delivery through WhatsApp, SMS, and IVR Messaging in High-Need Populations."

[77] C. R. Nwangele, A. Adewuyi, A. Ajuwon, and A. O. Akintobi, "Advances in Sustainable Investment Models: Leveraging AI for Social Impact Projects in Africa."

[78] M. A. ADEWOYIN, E. O. OGUNNOWO, J. E. FIEMOTONGHA, T. O. IGUNMA, and A. K. ADELEKE, "Advances in Thermofluid Simulation for Heat Transfer Optimization in Compact Mechanical Devices," 2020.

[79] A. Ajuwon, A. Adewuyi, C. R. Nwangele, and A. O. Akintobi, "Blockchain Technology and its Role in Transforming Financial Services: The Future of Smart Contracts in Lending."

[80] L. S. Komi, E. C. Chianumba, A. Y. Forkuo, D. Osamika, and A. Y. Mustapha, "A Conceptual Framework for Addressing Digital Health Literacy and Access Gaps in US Underrepresented Communities."

[81] T. Adenuga, A. T. Ayobami, and F. C. Okolo, "AI-Driven Workforce Forecasting for Peak Planning and Disruption Resilience in Global Logistics and Supply Networks."

[82] O.-e. E. Akpe, A. A. Azubike Collins Mgbame, E. O. Abayomi, and O. O. Adeyelu, "AI-Enabled Dashboards for Micro-Enterprise Profitability Optimization: A Pilot Implementation Study."

[83] J. Huttunen, J. Jauhiainen, L. Lehti, A. Nylund, M. Martikainen, and O. M. Lehner, "Big data, cloud computing and data science applications in finance and accounting," *ACRN Journal of Finance and Risk Perspectives,* vol. 8, pp. 16-30, 2019.

[84] F. U. Ojika, W. O. Owobu, O. A. Abieba, O. J. Esan, B. C. Ubamadu, and A. I. Daraojimba, "The Role of AI in Cybersecurity: A Cross-Industry Model for Integrating Machine Learning and Data Analysis for Improved Threat Detection."

[85] K. S. Adeyemo, A. O. Mbata, and O. D. Balogun, "The Role of Cold Chain Logistics in

Vaccine Distribution: Addressing Equity and Access Challenges in Sub-Saharan Africa."

[86] G. O. Osho, J. O. Omisola, and J. O. Shiyanbola, "A Conceptual Framework for AI-Driven Predictive Optimization in Industrial Engineering: Leveraging Machine Learning for Smart Manufacturing Decisions," *Unknown Journal,* 2020.

[87] E. O. Ogunnowo, "A Conceptual Framework for Digital Twin Deployment in Real-Time Monitoring of Mechanical Systems."

[88] M. A. Adewoyin, E. O. Ogunnowo, J. E. Fiemotongha, T. O. Igunma, and A. K. Adeleke, "A Conceptual Framework for Dynamic Mechanical Analysis in High-Performance Material Selection," 2020.

[89] G. P. Ifenatuora, O. Awoyemi, and F. A. Atobatele, "A Conceptual Framework for Professional Upskilling Using Accessible Animated E-Learning Modules."

[90] E. Y. Gbabo, O. K. Okenwa, and P. E. Chima, "Constructing AI-Enabled Compliance Automation Models for Real-Time Regulatory Reporting in Energy Systems."

[91] A. Y. Onifade, J. C. Ogeawuchi, and A. A. Abayomi, "Data-Driven Engagement Framework: Optimizing Client Relationships and Retention in the Aviation Sector."

[92] O. M. Oluoha, A. Odeshina, O. Reis, F. Okpeke, V. Attipoe, and O. H. Orieno, "Designing Advanced Digital Solutions for Privileged Access Management and Continuous Compliance Monitoring."

[93] M. A. Monebi, C. Alenoghena, and J. Abolarinwa, "Redefining The Directivity Value of Radial-Lines-Slot-Array Antenna for Direct Broadcast Satellite (Dbs) Service," 2018: 4. Monebi Matthew Ayodeji, Caroline O. Alenoghena, and JA Abolarinwa (2018 ….

[94] K. A. Bunmi and K. S. Adeyemo, "A Review on Targeted Drug Development for Breast Cancer Using Innovative Active Pharmaceutical Ingredients (APIs)."

[95] O. O. FAGBORE, J. C. OGEAWUCHI, O. ILORI, N. J. ISIBOR, A. ODETUNDE, and B. I. ADEKUNLE, "Developing a Conceptual Framework for Financial Data Validation in Private Equity Fund Operations," 2020.

[96] D. Bolarinwa, M. Egemba, and M. Ogundipe, "Developing a Predictive Analytics Model for Cost-Effective Healthcare Delivery: A Conceptual Framework for Enhancing Patient Outcomes and Reducing Operational Costs."

[97] B. M. O. S. O. Idemudia, O. K. Chima, O. J. Ezeilo, and A. Ochefu, "Entrepreneurship Resilience Models in Resource-Constrained Settings: Cross-national Framework," *World,* vol. 2579, p. 0544.

[98] D. I. Ajiga, O. Hamza, A. Eweje, E. Kokogho, and P. E. Odio, "Forecasting IT Financial Planning Trends and Analyzing Impacts on Industry Standards."

[99] J. O. Omisola, E. A. Etukudoh, O. K. Okenwa, G. I. T. Olugbemi, and E. Ogu, "Future Directions in Advanced Instrumentation for the Oil and Gas Industry: A Conceptual Analysis."

[100] A. Ajuwon, A. Adewuyi, T. J. Oladuji, and A. O. Akintobi, "A Model for Strategic Investment in African Infrastructure: Using AI for Due Diligence and Portfolio Optimization."

[101] O. T. Kufile, B. O. Otokiti, A. Y. Onifade, B. Ogunwale, and C. H. Okolo, "Modelling Attribution-Driven Budgeting Systems for High-Intent Consumer Acquisition."

[102] E. Y. Gbabo, O. K. Okenwa, and P. E. Chima, "Integrating CDM Regulations into Role-Based Compliance Models for Energy Infrastructure Projects."

[103] T. J. Oladuji, A. O. Akintobi, C. R. Nwangele, and A. Ajuwon, "A Model for Leveraging AI and Big Data to Predict and Mitigate Financial Risk in African Markets."

[104] O. Oluoha, A. Odeshina, O. Reis, F. Okpeke, V. Attipoe, and O. Orieno, "Optimizing Business Decision-Making with Advanced Data Analytics Techniques. Iconic Res Eng J. 2022; 6 (5): 184-203," ed.

[105] J. O. Omisola, J. O. Shiyanbola, and G. O. Osho, "A Predictive Quality Assurance Model Using Lean Six Sigma: Integrating FMEA, SPC, and Root Cause Analysis for Zero-Defect Production Systems," *Unknown Journal,* 2020.

[106] J. O. Omisola, E. A. Etukudoh, O. K. Okenwa, G. I. T. Olugbemi, and E. Ogu, "Geomechanical Modeling for Safe and Efficient Horizontal Well Placement Analysis of Stress Distribution and Rock Mechanics to Optimize Well Placement and Minimize Drilling," *Unknown Journal,* 2020.

[107] J. O. Omisola, E. A. Etukudoh, O. K. Okenwa, and G. I. Tokunbo, "Geosteering Real-Time Geosteering Optimization Using Deep Learning Algorithms Integration of Deep Reinforcement Learning in Real-time Well Trajectory Adjustment to Maximize," *Unknown Journal,* 2020.

[108] J. O. Omisola, P. E. Chima, O. K. Okenwa, and G. I. Tokunbo, "Green Financing and Investment Trends in Sustainable LNG Projects A Comprehensive Review," *Unknown Journal,* 2020.

[109] D. B. Bassey *et al.*, "The impact of Worms and Ladders, an innovative health educational board game on Soil-Transmitted Helminthiasis control in Abeokuta, Southwest Nigeria," *PLoS neglected tropical diseases,* vol. 14, no. 9, p. e0008486, 2020.

[110] A. M. Monebi and S. Z. Iliya, "An Improved Mathematical Modelling of Directivity for Radial Line Slot Array Antenna," 2020.

[111] G. O. Osho, J. O. Omisola, and J. O. Shiyanbola, "An Integrated AI-Power BI Model for Real-Time Supply Chain Visibility and Forecasting: A Data-Intelligence Approach to Operational Excellence," *Unknown Journal,* 2020.