Data-Driven Approaches in Offshore Infrastructure Inspection: From Manual Logs to AI Models

Dulo Chukwuemeka Wegner
Inspection Engineer
Fugro

Adumike Kenechukwu Nicholas
Data analyst
University of Hull

Ojoh Odoh
Data Analyst
University of Hull

ABSTRACT

Field verification and maintenance of offshore structures, including subsea pipelines, risers, and wind turbine foundations, are required to keep the operations safe, protect the environment, and prolong the life of the assets. Historically, inspections concentrated on diver commentaries and physical documents and photographs, which, although rudimentary, suffered from subjectivity, inconsistency, and long-range data storage. Software for inspections was a positive development, which, for the first time, enabled standardized performance for data capture, systematization of data and metadata, and integration of ROV and sensor data. Systems like FDVR, COABIS, and SENSE enhanced the ability of data capture and retention and, thereby, improved the decision-making for operators and regulators. In recent years, the offshore sector has been going through a new phase because of the influence of artificial intelligence and machine learning. These models are capable of assisting with anomaly detection, corrosion assessment, and fatigue prediction with abundant multiple untidy data from video, ultrasonic, acoustic, and various environmental sensors. More of these machine-learning systems are used within the digital twin technology and framework, which helps with real-time observation and monitoring, and proactive warning systems. More advanced subsea analytical systems, combined with conventional inspection data, allow operators to transition from unplanned maintenance to proactive predictive maintenance, which optimizes asset management, minimizes unplanned outages, and significantly increases safety. This analyzes the evolution of offshore inspection practices from manual to AI-driven approaches and the continuities between traditional inspection records and modern inspection predictive data systems. While challenges related to data quality and standardization, workforce training, and data security protection are recognized, the potential gains in resilience, cost effectiveness, and regulatory compliance are compelling. Integration of legacy data with digital inspection systems and AI-driven analytics evokes a paradigm shift in offshore infrastructure management by utilizing data as the principal element for safe, economical, and environmentally responsible operations.

Keywords

Data-Driven Approaches, Offshore Infrastructure, Inspection, Manual Logs, AI Models, Digital Transformation, Predictive Analytics, Machine Learning, Deep Learning, Computer Vision, Sensor Data, Big Data Integration, Cloud Computing, Digital Twin, Structural Health Monitoring

1. INTRODUCTION

The most critical aspect of offshore infrastructure is the sustained safe operation of coupled oil and gas production systems with renewable assets (Amaechi *et al*., 2022; Mahmood *et al*., 2023). Subsea energy interlinks of pipelines, risers, manifolds, and wind turbine foundations are perhaps the most sophisticated offshore structures, and the harshest and most unpredictable of Earth's environments (KM *et al*., 2022; Zhang *et al*., 2024). These include high-altitude and high-pressure conditions, dynamic ocean currents, corrosion-inducing seawater, and mechanical fatigue from waves and wind (Liu et al., 2023; Yu et al., 2023), which ultimately lead to degradation and failure. Any one of these assets having a structural or functional failure can result in enormous environmental pollution, production downtime, and risks to human life. This is why, for a long time, offshore asset management has been synonymous with the practice of monitoring the integrity of assets and decay signals to the point of maintaining critical infrastructures and extending their operational life (Adewoyin, 2022; Igbadumhe and Feijo, 2023).

The essence of these practices is data. Data becomes the only proof of the condition of an asset at a specific point in time and a factual basis around which informed understanding of risk and its management, maintenance scheduling, and regulatory compliance are built (Sasidharan *et al*, 2022; Kothandapani, 2022; Cornwell *et al*, 2023). The data recorded in diver logs (Dalhatu *et al*., 2023), remotely operated vehicles (ROV) surveys, data classified and analyzed Form of Non Destructive Testing (NDT), and sensory equipment are the decisive components of the inspection. Inspection depends on the effectiveness of the data. The evolution of data in offshore inspection within the last decades has transformed the perception of asset integrity from record keeping to a digital, holistic approach. Advanced operators no longer wait for failure to occur to begin maintenance scheduling; they are able to monitor and analyze data in real time to schedule proactive and predictive maintenance (Sandu *et al*., 2023; Zhou *et al*., 2024).

Records of the initial stages of offshore inspections focused on the use of written logs and annotated pictures, which were then put together in a report. This practice had a myriad of limitations owing to the subjectivity and difficulty in recording a reliable historical record, and discrepancies across inspectors. They were, to an extent, unprecedented in their use of tactile and visual methods of assessment. The expansion of the offshore sector in scale and complexity brought on abundant demand for standardization and accessibility of inspection data, which catalyzed the use of digital inspection platforms. Such systems brought in the use of centralized repositories and structured metadata formats, which visual, acoustic, and measurement data into cohesive inspection packages. Enhancement in traceability and consistency across inspection campaigns, the software platforms such as COABIS, SENSE, and Field Data Validation and Reporting (FDVR) augmented regulatory oversight and improved inter-campaign comparability.

The fourth industrial revolution is heavily influenced by artificial intelligence (AI) and predictive analytics. Algorithms, paired with digital twin technology, have advanced to the point where inspection data is more than a series of still images of the condition of an asset (Hosamo *et al.*, 2022; Hagen and Andersen, 2024). Inspection data is now processed in real-time and is used to identify anomalies, corrosion rates, simulate structural fatigue, and warn of potential asset failure. AI systems analyze and synthesize datasets that comprise high-def ROV videos, cathodic protection scans, environmental data, and ultrasound scans to construct an asset integrity assessment (Abdullah *et al.*, 2024; Garrison *et al.*, 2024). Thus, the evolution data is not only technological but has now become a strategic asset in the efficiency, uptime, cost, and safety optimization of offshore operations.

This is intended to document the changes to deep-sea inspection methods of the use of paper logs through manual inspection and the use of software to perform digital inspections, to the current use of software, and the onboarding of AI-powered predictive systems. This also illustrates the transformation of data from an obsolete and passive record to a pivotal and versatile facilitator of proactive asset management. This paper attempts to make a case for the critical role that data-centric strategies and frameworks play in ensuring resilience and sustainability within the Offshore Sector. Considered Holistically, the stakes of integrity management for regulatory compliance and the multifaceted offshore industry remain unparalleled (Bechtsis *et al.*, 2022; Ake, 2024).

2.1 Evolution of Offshore Inspection Data Practices

The management of asset integrity is constantly evolving, as is the management of inspection data, and the offshore energy industry is no exception. Inspection data is being collected, managed, and utilized in previously unprecedented manners. Reliance in the offshore industry and the sophistication of structures have fueled advancement in offshore infrastructure, as has the rapid growth of structural engineering and digital and analytical technologies. Inspection practices have changed over the decades; instead of utilizing handwritten records and diver logs, smart and data-driven predictive approaches alongside advanced AI technology within digital twin frameworks are being utilized, as shown in Figure 1. The use of AI in inspection systems predicts data more accurately, contributing to decision-making. Differentiating between manual logs and records, digital inspection, and AI-based predictive systems illustrates the evolution of inspection data collection in offshore settings (Mahadevkar *et al.*, 2024; Jenifer *et al.*, 2024).

Record keeping in the offshore operations in the early decades relied largely on diver surveys. Critical sections of offshore operations were captured and documented through handwritten logs, sketches, and even film documentation (Nigam *et al.*, 2021; Balasubramanian, 2023). These logs and reports were the primary evidence of the operational assets in their working condition, as they were thoroughly compiled into the technical dossiers to be sent to regulators and operators for operational review and compliance.

Manual techniques remain invaluable for understanding the condition of underwater infrastructures; however, these techniques are far from perfect. Subjectivity in the human perception process introduced unnecessary gaps into the inspections; two divers could look at the same structures and see two completely different things, and still report the same anomalies. Interpretation of the write-ups after inspections had no meaning as the documents often were vague. Documents lacked structure and organization, and thus, the storage and paperwork were difficult to manage due to the fact that the underlying parameters and their various forms made it prone to losing data in floods and fires, files could simply be misplaced, and lastly, the preservation of the archives was done poorly.

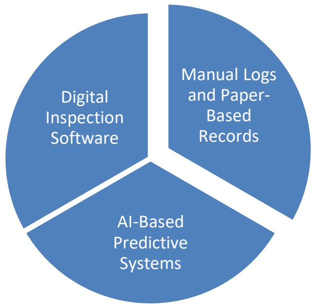

Figure 1: Evolution of Offshore Inspection Data Practices

The variability of each inspection cycle is also a critical factor. Language and formatting of documents provided in the inspections made it difficult to analyze and detect deterioration in the structures over periods of time (Lamm *et al.*, 2022; Musaev *et al.*, 2023). Photographs, when provided, were often missing critical elements such as the depth of the picture of the structure, the area where the structure was, or the weather. During the late 1970s and 1980s, these structures became more complex, and the inefficiencies observed in the 10 years prior were no longer acceptable. The need for precise and clear digital inspection documents shifted the way we approach inspections.

The 1990s saw the beginning of offshore inspections evolving from relatively rudimentary processes to much more advanced practices with the advent of computerized logging systems. The initial forms of digital systems overlaid paper logs with structured databases of the logs, which subsequently made inspections much more organized and easier to access. These systems supported the user in standardizing the use of other terminology, consistent templates, and incorporating metadata databases about the logs, such as GPS, Datetime, and other environmental data (Sidol *et al.*, 2021, and Shao *et al.*, 2023).

The use of ROVs in workflows as systems with video cameras, sonar, and elementary NDT sensors was a crucial development. ROVs augmented the ability to gather hundreds of data points in real time from high-risk subsea locations. With the ability to digitally preserve and later analyze complex systems, ROVs improved the ability of engineers and other stakeholders to conduct subsea analysis (Jahanbakht *et al,* 2021; Kabanov and Kramar, 2022). Driverless operations improved the safety and reliability of subsea inspections.

Specialized software platforms like COABIS, Field Data Validation and Reporting (FDVR), and SENSE made perimeter inspections and other inspections more digitalized COABIS and SENSE made captures and real-time annotations of videos and reports automated. All of them, by centralizing digital stores, made tracing multiple inspections more efficient. They also enabled cross-operator, cross-field, and condition benchmarking of assets (Frank, 2022, Ellahi *et al*., 2023).

The digital inspection software streamlined workflows. It also integrated devices into the databases to cut redundancy and print errors. All (or most) of them made past inspection data reliable for audits, so it kept the data accessible even after multiple time spans. It even made benchmarking easier for multiple operators, which improved safety and efficiency industry-wide. Digital systems made compliance with regulations easier, especially in the case of the U.K. and Norway, where evidence-based validation of offshore integrity management was required.

Progressing from earlier stages, digital inspection systems were still mostly descriptive. They were capable of recording and storing data, but offered little in the way of predictive forecasting and insight generation. More advanced methods were needed to capture and correlate data generated during inspections and provided by ROVs and sensors to gain actionable intelligence from the inspection data generated from ROVs and sensors (Xiang *et al*., 2022; Ma *et al*., 2023).

The most recent phase of the development of offshore inspection practice is the application of artificial intelligence and predictive analytics to offshore inspections (Fazle *et al*., 2023; Aditiyawarman *et al*., 2023). Machine learning is becoming critical for anomaly detection and condition forecasting, due to the growing abundance of quality and volume data streams provided by ROVs, AUVs, and subsea sensors.

AI technologies can analyze different types of data, including sounds, measurements of the ultrasonic thickness of walls, cathodic protection readings, and videos. These and many other types of data can be merged together to form large databases, containing the information about the interactions of mechanical, chemical, and environmental factors which lead to the degradation of a particular substrate, as shown in Table 1. With the help of the machine learning derived algorithms, the datasets can monitor the early stages of the coating corrosion, coating detachment, and any possible structural weakness which other people would not be able to notice (Islam *et al*., 2022, Gbagba *et al*., 2023).

Digital twin frameworks construction has further enhanced the offshore inspection capability of Artificial Intelligence. These are real-time smart models of physical assets that are updated and improved with data from inspections and sensors. Equipped with the appropriate predictive analytics algorithms, predictive models can help operators determine degradation processes, estimate time to failure, and assess the impact of various maintenance action plans on the system. Predictive models help overcome the limitation of relying on historical data and past trends observed in the description models, which do not offer actionable strategies to ensure sustainability (Kubrak *et al*., 2022, Ahern *et al*., 2022.)

The benefits associated with AI-driven predictive systems are profound. The ability to identify failure hindrances at early stages enables maintenance to be planned and scheduled before breakdowns and other expensive malfunctions. This decreases unplanned downtime, increases the safety of operations, and prolongs the life of offshore assets. Predictive systems improve the efficiency of costs by optimizing the scheduling of inspections of components of higher risk tiers (Suryadevara 2021; Korada and Somepalli 2022). Furthermore, AI improves the specificity and consistency of detecting anomalies, which lessens the reliance on the assessment of a single inspector.

Still, challenges persist with completely realizing the potential of systems driven by Artificial Intelligence. The quality of data, the standardization of operators, and the available interoperability of software platforms are real concerns. The workforce needs to be trained so that engineers can understand and implement the AI insights that are generated. Cybersecurity becomes a critical scenario in the hands of engineers as more data about inspections is being collected and stored in the cloud systems (Dhoni and Kumar 2023; Karunamurthy *et al*., 2023).

The development of operational procedures for offshore inspection data still strives for enhanced dependability, effectiveness, and safety workflows. Subjectivity and limited comparability impacted the formulation of documenting asset condition by the use of Manual logs, coupled with paper records. Furthermore, the introduction of digital inspection software augmented the use of standardization, traceability, and data assimilation, especially with ROVs and organized databases. Today, AI-based predictive systems profoundly shift the paradigm by using proactive asset management through sensor fusion and digital twin integration for anomaly detection. These examples position data as more than a data record, as evidenced by these advances, but rather as a predictive asset for forecasting and counter-risking in more intricate offshore environments (Rawson and Brito, 2022; Hadjoudj and Pandit, 2023).

Table 1: AI-Based Predictive Systems

Theme	Key Aspects	Benefits	Challenges
Emergence of Machine Learning and Artificial Intelligence in Anomaly Detection	- Deployment of supervised and unsupervised ML models.- Automated classification of defects in subsea pipelines, welds, and structures.- Use of AI for anomaly pattern recognition beyond human capability.	- Detects subtle and early-stage anomalies.- Enhances accuracy and consistency in inspections.- Reduces reliance on manual interpretation.	- Requires large, high-quality training datasets.- Potential for algorithmic bias and false positives.- High computational demand.
Integration of Sensor Fusion with Predictive Analytics	- Combining acoustic, ultrasonic, thermal, and visual sensors.- Cross-validation of anomalies across multiple data sources.- Advanced analytics	- Improves reliability of anomaly detection.- Reduces uncertainty through multimodal confirmation. - Enables continuous monitoring	- Complex calibration of heterogeneous sensors.- Synchronization and data alignment issues.- Higher system integration costs.

Theme	Key Aspects	Benefits	Challenges
	pipelines for real-time decision support.	even in noisy environments.	
Application in Digital Twin Frameworks for Continuous Condition Monitoring	- Virtual replication of offshore assets using AI-enhanced models.- Real-time synchronization between physical and digital asset states.- Simulation of degradation and failure scenarios.	- Enables predictive maintenance strategies.- Facilitates long-term asset lifecycle planning.- Provides visualization for operator training and risk assessment.	- High demand for computational power and storage.- Dependence on accurate baseline models.- Cybersecurity and data integrity concerns.
Advantages: Early Failure Prediction, Reduced Downtime, and Optimized Inspection Scheduling	- Forecasting equipment failure before critical breakdown.- Automating inspection planning based on risk levels.- Adaptive scheduling aligned with real-time asset health.	- Minimizes unplanned maintenance costs.- Increases offshore operational efficiency.- Extends asset lifespan while ensuring safety.	- Requires cultural and organizational shift toward data-driven maintenance.- Initial investment in AI infrastructure is high.- Uncertainty in regulatory acceptance.

2.2 Bridging Traditional Inspection with Smart Subsea Analytics

Customarily, the offshore energy sector relied on manual inspection logs, observing divers, and reports on the condition of subsea infrastructure done at varying intervals. Though these methods have worked in the past, the complexity of aging assets, coupled with growing operational complexity and the industry's shift toward renewables, makes these techniques less than useful. Recent advancements in smart subsea analytics driven by AI, the cloud, and real-time sensors provide the opportunity to change inspection workflows from reactive to predictive frameworks. Bridging the observational inspection legacy data, upon which historical asset integrity management rests, with current digital technologies is a significant challenge, as shown in Table 2. These transition strategies, bordering technologies, and case studies on the effective incorporation of traditional inspection with advanced smart subsea analytics.

For most offshore operators, decades worth of inspection logs, diver notations, and disparate data formats that are either frozen in static reports and spreadsheets, or archived are a common occurrence. It is imperative that these legacy datasets are reformed into usable digital assets with structured data curation, metadata tagging, and systems for digitization. Data governance policies that clarify ownership, quality control and procedures, and standardization across the organization must be a primary focus. To contextualize the methodology of Kumaran and Machireddy, companies are increasingly utilizing Extract-Transform-Load (ETL) pipelines to convert unstructured inspection data into defined databases. Another strategy for improvement focuses on the digitization of prioritized, high-value datasets like corrosion reports and ultrasonic testing logs, as these predictive models contain critical information. In this manner, organizations are able to develop inspection databases that provide advanced analysis based on historical data.

Table 2: Bridging Traditional Inspection with Smart Subsea Analytics

Theme	Key Aspects	Benefits	Challenges
Transition Strategies for Companies with Legacy Inspection Data	- Migration of paper-based/manual logs into digital databases.- Standardization of archival inspection formats.- Training workforce to integrate historical data into modern systems.	- Preserves decades of operational knowledge.- Enables trend analysis and predictive modeling.- Reduces redundancy in future inspections.	- Data inconsistency and quality gaps.- High cost of digitization.- Resistance to organizational change.
Photogrammetry and 3D Reconstruction of Historical Records	- Converting old 2D inspection images into 3D digital twins.- Reconstruction of subsea assets for baseline comparison.- Integration with GIS and CAD systems.	- Provides visual continuity between past and present asset states.- Enables precise defect growth tracking.- Enhances training and simulation accuracy.	- Technical difficulty in aligning low-resolution historical images.- Computational resource demands.- Need for skilled image processing experts.
Combining Structured Metadata with Real-Time Sensor Data	- Tagging legacy records with metadata (location, asset type, defect class).- Linking metadata with real-time ROV/AUV sensor streams.- Multi-layered data analytics pipelines.	- Creates a holistic asset integrity profile.- Improves anomaly detection and failure prediction.- Supports cross-platform data interoperability.	- Metadata gaps in historical datasets.- Complexity in integrating heterogeneous data sources.- Cybersecurity vulnerabilities.

Theme	Key Aspects	Benefits	Challenges
Role of Cloud Platforms and Edge Computing	- Cloud storage for historical and real-time datasets.- Edge devices for on-site preprocessing of sensor data.- Remote dashboards for global collaboration and decision-making.	- Reduces latency in anomaly detection.- Scalable and secure data management.- Enables remote inspections and reduces offshore travel.	- Bandwidth limitations in offshore environments .- High dependency on network reliability.- Data governance and regulatory compliance concerns.

Reconstructions and photogrammetry have advanced sufficiently in skill and depth to convert analog records from visual inspections and convert them into digital, analyzable formats. Adding to digital photogrammetry structures, operators can also create digital twins from ROV video footage. These digital twins from subsea structures yield discrete and 3D geometric measurements. In addition to geometry, these twins can also show a change in state over time, especially when the historical datasets are augmented with modern datasets (Yu *et al*., 2021; Ronchi *et al*., 2023). An application of such a method would be if we take a 3D digital reconstruction model created using divergent underwater photographs of a site captured in the 1990s and juxtapose it with modern ROV models. We can geographically record the evolution of submerged structures in corals, the extent of rust, and even structural collapses. Standardized spatial datasets created using photogrammetry also record spatial data of legacy records. Such records can be aligned with modern inspection techniques such as laser and sonar scanning. The captured analog data can be embedded into frameworks of digital asset management systems, also termed as 'rescued' data.

Instruments of subsea analytics depend on the integration of different data sets. Digitized onboard documentation can be improved and enriched by correlating it with real-time data generated by remote-operating vehicles (ROVs), autonomous underwater vehicles (AUVs), and dedicated monitoring systems. Structured metadata like the date and place of the inspection, the prevailing environmental parameters, and the type of defect helps derive context for real-time interpretation. As an example, an attempt to relate real-time cathodic protection and ultrasonic thickness measurements to a historic record that describes the onset of corrosion on a weld on a pipeline would make better sense if the record were to be metaphysically enriched with corrosion indication and protection data. Fusing metadata streams with defect inspection data enhances analytics by means of real-time stream access, lagged and correlated access for temporal trend-analysis, and the application of machine learning for predictive analytics (Nizam *et al*., 2022; Liang *et al*., 2023). The marriage of legacy information and contemporary data provides a bedrock for risk-informed decisions for offshore asset management.

More extensive data records need to be stored, processed, and accessed quickly. In response, many companies use cloud technology because it allows users to easily and quickly electronically store, operate, and manage examination databases, AI models, and collaborate worldwide. Cloud-based digital twins allow users from many locations to electronically store, analyze, and collaboratively view repair virtual models in almost real-time. In addition to cloud technology, edge computing supplies data processing almost in real-time and close to the underwater sites of interest (Periola *et al*., 2022; Dar *et al*., 2023). AI-enabled remotely operated vehicles (ROVs), for instance, can analyze video in real-time, flagging possible defects and then sending only compressed data sets to the cloud for further examination and study, thanks to edge processors. This edge computing in cloud technology system allows for quicker offshore decisions while also creating much less lag, lower bandwidth demand, and examining data in a quicker sequence remotely. This edge computing in cloud technology system allows for faster offshore decisions while also creating much less lag, lower bandwidth demand, and faster examination of remote data sets. These two models, edge and cloud computing, together provide a holistic solution that integrates digital measurement and analysis systems while also digitalizing standard measurement and analysis processes.

An example of this change is how diver logs and ROV inspection datasets are integrated for corrosion prediction. Diver logs tend to lack a standardized causation and are often hyperdescriptive. Still, they provide a valuable qualitative description of the asset's condition. Once digitized, descriptive diver logs can be indexed with metadata and cross-referenced with ROV inspection datasets to yield ultrasonic thickness and cathodic protection measurements. Feeding the datasets into machine learning algorithms allows operators to predict corrosion rates for varying corrosion rates for different environmental and operational scenarios. These models are better than modern sensor data analyses because they utilize historical baselines capturing asset-specific degradation baselines Gadam and Upadhyay, 2023; Bienert *et al*., 2023). For example, a North Sea offshore operator incorporated ROV cud photogrammetry datasets with three decades of diver logs to train a neural network predicting corrosion hotspots with over 85% accuracy. This illustrates the importance of coupling the old inspection methods with modern analytical techniques.

The combination of traditional inspection with smart subsea analytics is as much a technological imperative as it is an operational opportunity. Digitization and the standardization of legacy inspection records and data as part of the transition strategy enable advanced analytics adoption, just as photogrammetry and 3D reconstruction of historical images provide new value. Embedding structured metadata with sensor data provides enhanced situational awareness, and cloud-edge computing frameworks support effective, remote, and cooperative decision processes. Case studies, such as the application of AI models with diver log and ROV dataset integration, illustrate the value of this convergence for predictive corrosion management. It is the offshore industry's ability to merge legacy inspection analytics with smart diagnostics that will determine the ability to be resilient, cost-effective, and sustainable to asset integrity management in an operationally and environmentally stressed business climate (Rehman and Islam, 2023; Attah *et al*., 2023).

2.3 Challenges and Limitations

The management of the integrity of offshore infrastructures has evolved significantly from manual inspection logs to the use of digital technology, and most recently to the use of AI-driven predictive systems. However, these advancements do come with a fair share of issues. The offshore environment indeed possesses its own set of challenges from the engineering, economic, and regulatory standpoints, which makes advanced inspection driven by data use very effective (Ezeanochie *et al*., 2022; Ofoedu *et al*., 2022). The concerns of these challenged can roughly be categorized into four, which are; the data accuracy and standardization issues, the exorbitant prices of advanced sensors and AI systems fusion, the complex data require specialized workers to decipher, and the unavoidable cloud-based systems that increases the complexity and data control issues to the users, that incite a fear of the growing cybersecurity threats as shown in figure 2.

The most important part of inspection work is the information that has to be collected and the authenticity of that information. Inspections that are done offshore use a variety of data conducting tools, which include high-quality videos, ultrasound to measure the thickness of walls and cups, invasive and non-invasive sensors to measure cathodic protection, and even environmental sensors. The other data sets that can be collected are abundant, satisfying the requirements of inspection that can be set. The only thing that poses a challenge is the calibration of the data collected and its comparability depending upon the operators, assets, and time intervals (Idowu *et al*., 2022, Sarker *et al*., 2022).

Sensor readings that are influenced by environmental factors such as turbidity, growth of marine organisms, and equipment issues are also unable to record quality data. Faulty and careless human actions like misreading logged data, inconsistent calibrations, and visual data anomalies add much deviation and loss in precision (Liu *et al*., 2021; Gore *et al*., 2021). Even in modern digital forms, context, as well as metadata such as time, environmental factors, and geolocation, are not always thoroughly captured, thus hindering the reconstruction and validation of inspection data.

Standardization also remains an important concern. Different operators are known to apply their proprietary formats to the data and even create novel names to describe data structures and reporting schemas. This lack of harmonization hinders the integration of inter-company datasets, inspections, and cross-sector benchmarks. Despite attempts by regulators and industry consortia to standardize protocols, adoption remains patchy in the developed world, where regulatory oversight is lacking. The effectiveness of advanced analytics and AI is also limited without consistent standards, as the absence of reliable data, fragmentation, or poor-quality data leads to unreliable predictions (Balahur *et al*., 2022; Rangineni *et al*., 2023).

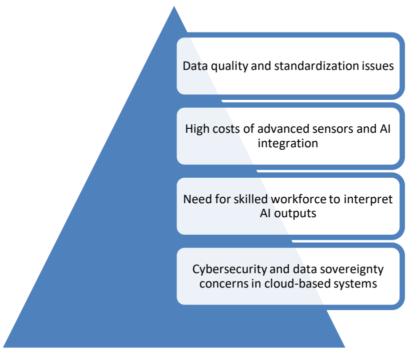

Figure 2: Challenges and Limitations

Another equally significant barrier to adoption remains the cost. High-resolution sensors like multi-beam sonar systems and advanced ultrasonic probes, or hyperspectral imaging systems, come at a significant cost (Sun *et al*, 2021; Kamolov and Park, 2021). Multi-beam sonar systems and advanced ultrasonic probes, or hyperspectral imaging systems, are typically deployed at sites using advanced, specialized remotely operated vehicles (ROVs) or autonomous underwater vehicles (AUVs), and thus, multi-beam sonar systems and advanced ultrasonic probes, or hyperspectral imaging systems, significantly increase operational complexity and cost.

The added costs associated with augmenting workflows with AI Inspection systems do not help the situation either. Machine Learning adoption involves the collation of massive data, which needs to be properly organized, labeled, and categorized, and therefore trained. The data inspection involves the incorporation of digital twin systems and the associated tech in the twin systems, which then merges and aligns with the systems beside the twin docs, which then merges spacecraft systems. There are also infrastructures associated with twin tech, which include massive resources, expensive processing costs of inspection data (Zhao *et al*, 2022; Mihai *et al*., 2022). The shipping businesses in new emerging markets cannot monetize the systems at scale.

Predictive analytics have benefits that include reduced downtime, lowered costs by extension of asset life, and reduced occurrence of catastrophic failures. The benefits are enough to offset the initial costs, but the cost still tends to create some resistance. As studies tend to fulfill the immediate operational needs before attending to strategic investments, even in much stable energy markets which have volatile budget restraints (Gabor, 2021; Akpe, 2022). So, cost remains the primary barrier to the equitable use of AI inspection technologies in the global offshore sector.

In the use of AI and predictive analytics for offshore inspections, the attributes of the software and hardware are just a fraction of the requirements. Expertise in capturing and analyzing the outputs of the complex algorithms generated by the software remains critical. Anomalies can be detected and degradation predicted through machine learning. However, they have no value unless they are contextualized to convert the prediction into a maintainable, actionable strategy.

There have always been gaps that need to be filled strategically in the offshore sector, and they have increased. A proportion of engineers and inspectors are very experienced in traditional inspections, but they lack the knowledge of data science, machine learning, and operating digital twins. There is a need to have investment specifically in the form of workforce frameworks that specialize in offshore engineering, together with advanced analytics to eliminate the gaps (Oksavik, 2021; Hazrat, 2023).

Furthermore, the use of AI can breed issues of contextual trust and diffusion of accountability. In the case where an algorithm's forecasts contradict the judgments made by a human analyst, the person administering the AI decides which input to use. In reality, there is no use case of AI that does not depend on a workforce capable of interacting with the outputs of AI on a critical level. In the absence of such a workforce, there is the risk that the AI is underused or, in the worst case, not used at all. Both cases decrease the worth of the predictive systems. Consequently, there is a need to build a workforce that can integrate human wisdom with that of machines to capture the full value of data-led inspection (Johnson *et al*., 2021; Adekunle *et al*., 2021).

With the increase in the amount of inspection data that is stored in the cloud, issues of cybersecurity and data sovereignty have become more pronounced. Cloud systems have infrastructural lacunae. Cloud systems are appealing because of the way they are able to scale and become extremely accessible, in addition to providing the ability to integrate real-time monitoring to widely distributed geographical assets (George, 2022; Oladosu *et al*., 2023). Cyberattacks aimed at critical infrastructure data can have the ability to disable workflows, endanger safety measures, and have the ability to induce industrial espionage. In the worst case, advanced persistent threats can alter and manipulate inspection data to hide structural inadequacy, resulting in disaster.

Sovereignty is another aspect that adds complexity. Offshore operators often work across various jurisdictions, each with various laws regarding the storage, sharing, and transmission of sensitive information. European Union General Data Protection Regulation (GDPR) is one of the frameworks that applies stringent stipulations on the management of certain information, and other regions do not have well-defined parameters. The complexity of these arrangements is highlighted when used by multinational companies that attempt to balance cross-border cloud storage solutions (SHARMA *et al*., 2021; Mercurio and Yu, 2022).

In addition, the cloud-based systems raise certain issues on ownership and control over the inspection data. Protecting sensitive data from being misused and accessed without authorization is a great challenge to the operators when data is stored, analyzed, and processed using AI by third-party service providers. This challenge is only resolved when there are adequate political, economic, and social security systems that work as cohesive frameworks. The processes are needed inherently, but are also complex and raise cost issues.

The transformation of offshore inspection practices, on the other hand, in adapting AI has a few obstacles on the way. High costs of adopting such technologies as machine learning mean widespread implementation on a mass scale is economically unrealistic. It is also true that, ruling out the entire reliance on human expertise, machine learning comes with its own set of challenges, such as the inability to interpret AI outputs. Subjects such as Cyber Security become a real issue when talking about the storing of sensitive cloud-based offshore inspection data. Only through collaboration can regulatory bodies, operators, technologists, and other institutions remedy such challenges. Only through such a remedy can the offshore sector benefit from inspection data without militarized guarding of its assets and operations.

2.4 Future Outlook

Offshore asset inspection and asset integrity management are dynamically changing due to advancements in robotics, data analytics, and digital infrastructure, as shown in Figure 3(Gower, 2023; Sinha, 2023). The traditional models of inspection and cost for offshore energy systems, which include deep-water oil and gas facilities as well as floating wind farms, are becoming unresponsive as inspection scales and systems evolve more rapidly to diversify. A more optimistic assessment identifies three trends: development of autonomous inspection systems; movement toward globally standardized inspection databases, and predictive analytics more deeply integrated with resilience frameworks from the DOE and DHS. Each of these trends has significant implications for how offshore assets are monitored, maintained, and protected from operational and environmental threats.

The next generation of subsea inspection technology will hinge on AUV and ROV hybrids with machine learning capabilities. These robotics platforms can better sustain margin performance while enhancing safety superbly by reducing the tethered and surface vessel supports. AUV-ROV hybrids are already equipped with AI systems designed for autonomous navigation, adaptive mission planning, and real-time defect detection. These vehicles with onboard processing can flag in situ anomalies. Thus, the surface team is clogged by minimized volumes of raw data below real-time decision-making by the inspection systems (Ford *et al*., 2022; Caldwell, 2023). In the future, fleets of autonomous robotic inspection systems can barrage subsea infrastructure continually for early signs of corrosion, structural degradation, and the accumulation of marine growth. In a more profound societal sense, this shift increases the large societal structural frame with viable avenues for continuing growth to position AI robotics systems as pivotal for the offshore energy transition.

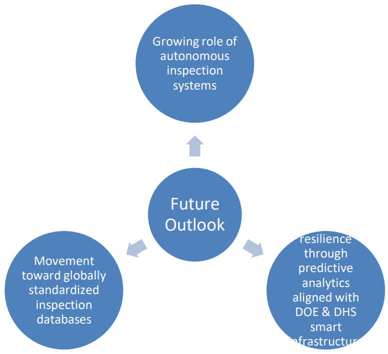

Figure 3: Future Outlook

A worldwide focus that is equally important is the movement towards unified databases of inspections. Inspection data is still held in silos across different operators, regions, and regulatory frameworks, with almost no ability to work across regulatory frameworks. These data siloes inhibit the likelihood of benchmarking, mutual learning, and oversight across different jurisdictions. Greater initiatives focus on the offshore industry with the development of unified data taxonomies, structures of metadata, and reporting treaties to enable seamless cross-industry data exchange. International bodies like the International Maritime Organization and the International Association of Oil & Women in Oil and Gas Producers are in a strong position to lead this work, with collaborative industry consortia. Unified databases would be advantageous for the cross-industry to improve advanced machine learning tools for greater data saturation. Predictive maintenance in the offshore regulator industry would be greatly enhanced with unified global data frameworks, which would also strengthen trust among various regulators, operators, and stakeholders (Zhu and Liyanage, 2021; Nwulu *et al*., 2023).

Offshore inspection predictive analytics complements the resilience goals advocated by the DOE and DHS (Hummel and DiRenzo, 2023; Radvanovsky and McDougall, 2023). Both agencies stress the critical need for disruption-anticipating, smart infrastructure that can address operational hurdles like equipment failures, extreme environmental conditions, and severe cyber-physical threats. Machine learning algorithms, digital twin technology, and sensor fusion-enabled predictive analytics can estimate the degradation of an asset and anticipate strategic response behaviors to a wide range of simulated asset scenarios. For instance, predictive corrosion models can identify vulnerable pipeline sections before failure occurs, and digital twin models can simulate the strategic execution of emergency repairs to minimize operational disruptions. These digitally enabled capabilities, when aligned with resilience frameworks, allow offshore operators to integrate with and support broader, national, and international energy, infrastructure, and environmental resilience goals. The integration of predictive analytics with resilience initiatives will, in turn, stimulate offshore energy system investments, facilitate digital regulatory frameworks, and improve public trust in these systems (Argyroudis *et al*., 2022; Mintoo *et al*., 2022).

The forthcoming paradigm for offshore inspection seems technologically advanced while predicting the fractures in robotics, standardization, and predictive resilience. Autonomous inspection systems, anticipating more reach, more efficient, and safer monitoring of subsea ecosystems, will have global databases on predictive analytics for DOE and DHS smart infrastructure to solve the problems of interoperability and cross-border data collaboration. Offshore assets will, therefore, be optimally and smartly, as well as dynamically managed, predicting the evolving threats based on the analytics (Spaniel, 2022; Evans *et al*., 2022). These frameworks will make offshore inspection frameworks more reactive in essence, yet more intelligent and coordinated on a global scale. The offshore industry, therefore, equipped with more sophisticated tools to monitor the health of aging assets, will be able to aid the energy transition with more renewable sources, as well as maintain the domain with more sustainable and distributed resilient energy infrastructure across the globe.

3. CONCLUSION

The development of practices for inspecting the energy systems offshore shows a change in how these practices are carried out, especially how marine infrastructures are integrated. The first method of recording the subsea systems manually, where a recording shift attendant accompanied a diver down, illustrated the rudimentary practices that would come to define subsea. The process of recording these manually came with several pros and minuses, subjectivity, data erosion, and the limits of foggy composites. Accuracy in the process was and still is revered, however, regardless of data standards in imagery or recollection. The diversification of subsea inspections brought engagement of ROVs with digital platforms built into SOVs (Submersible Optical Vehicles). Devices such as Coabis, FDVR, Sense, and other structured software digitized the lore of the as-built detection and inspection, while standard metrics still lag. The Merit of modern, integrated, offshore structures with Artificial Intelligence suggests a new frontier in inspections where a digital twin device was integrated into subordinate, rigid ROVs that are deployed subsea. Operations and methodologies of inspection can now track and forecast failures, optimize maintenance, and identify critical points in safety protocols.

The shift from legacies of the past to the new approaches that are brought out should be identified as a fusion, not a deletion. Old accounts, regardless of inaccuracy, set the framework to design the new systems that would capture the erosion in structures, systems, and safety with great depth. The new systems would need the old data to ensure maximum coherence with modern digital and AI models.

The vision, which seems more plausible in the case of future offshore inspection, would be a framework that is fully data-driven and predictive while also being sustainable. This vision would incorporate offshore data standards, robust cross-governance frameworks, and cross-sector interoperable collaboration between diverse regions and technologies. In addition, real-time data based on sensor fusion, AI autonomy, and cloud-based data management systems would be the expected standard. Integrating frameworks with sustainability and resilience, offshore inspections would be expected to advance towards more proactive rather than reactive problem-solving in energy infrastructure stewardship. This 'realignment' in approach is best reflected in the AI predictive models and handwritten diver logs divergence. This has resulted in a vision that is more technologically advanced, while also being safer and reliable concerning offshore operations.

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