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Sustainable Offshore Energy Operations in Europe: Leveraging AI for Resilient Supply Chains and Asset Management

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Abstract

Artificial intelligence is increasingly transforming offshore energy operations by enhancing operational efficiency, safety, environmental stewardship, and supply chain resilience. As Europe has accelerated its transition towards a sustainable and low-carbon energy system, the integration of intelligent digital technologies across offshore oil, gas, and renewable energy sectors has become increasingly important. This review critically examines the application of artificial intelligence in sustainable offshore energy operations, with particular emphasis on predictive maintenance; demand forecasting; inventory management; transportation and logistics optimisation; real-time monitoring; digital twins; and health, safety, and environmental management. Relevant evidence was synthesised through a structured review of peer-reviewed literature and authoritative industry publications, with findings organised via a thematic analytical approach. This review demonstrates that artificial intelligence enables more proactive asset management, improves maintenance planning, enhances logistics coordination, strengthens operational decision-making, and supports environmental monitoring through real-time data analytics and autonomous systems. However, challenges related to data quality, cybersecurity, interoperability, workforce capability, regulatory uncertainty, and implementation costs continue to constrain widespread deployment. The study highlights the importance of integrating artificial intelligence with digital infrastructure and organisational capabilities to maximise operational value and sustainability outcomes. This study concludes by identifying key research priorities and practical considerations that can support the responsible adoption of artificial intelligence in Europe's evolving offshore energy sector.

Keywords: Digital transformation, Climate change, Supply chains, Digital technology, Offshore energy, Artificial intelligence, Real-time analytics, Sustainability

1. Introduction

Offshore hydrocarbon activities remain vital to the global energy supply, producing approximately 30% of the world's crude oil, as shown in Figure 1 (Statista, 2025). Much of this output occurs in challenging marine environments, from shallow shelves to deepwater basins over 3,000 metres deep. These frontier areas feature complex subsurface geology, including fault systems, salt diapirs, and segmented reservoirs, increasing exploration and production risks (Rahman & Fuad, 2018). As onshore fields mature and geopolitical issues impact land-based energy sources, offshore operations are increasingly strategic, especially for energy-dependent regions such as Europe (Harichandan et al., 2022). The offshore industry has evolved through successive waves of technological progress and geographic expansion, starting with basic platforms in California in the 1890s and culminating in the first modern offshore rig in the Gulf of Mexico in 1947. This ongoing

development has pushed into more challenging environments, notably in the North Sea, Gulf of Guinea, and Arctic Circle, opening access to large reserves once considered too costly or unreachable. However, this expansion involves significant physical challenges, such as severe weather, strong currents, and turbulent winds (Seyyedattar et al., 2020). Operations are often located more than 50 kilometres from shore, complicating logistics and emergency responses (Necci et al., 2019). In these harsh settings, equipment failure, supply delays, or human errors can lead to serious financial, environmental, and reputational damage.

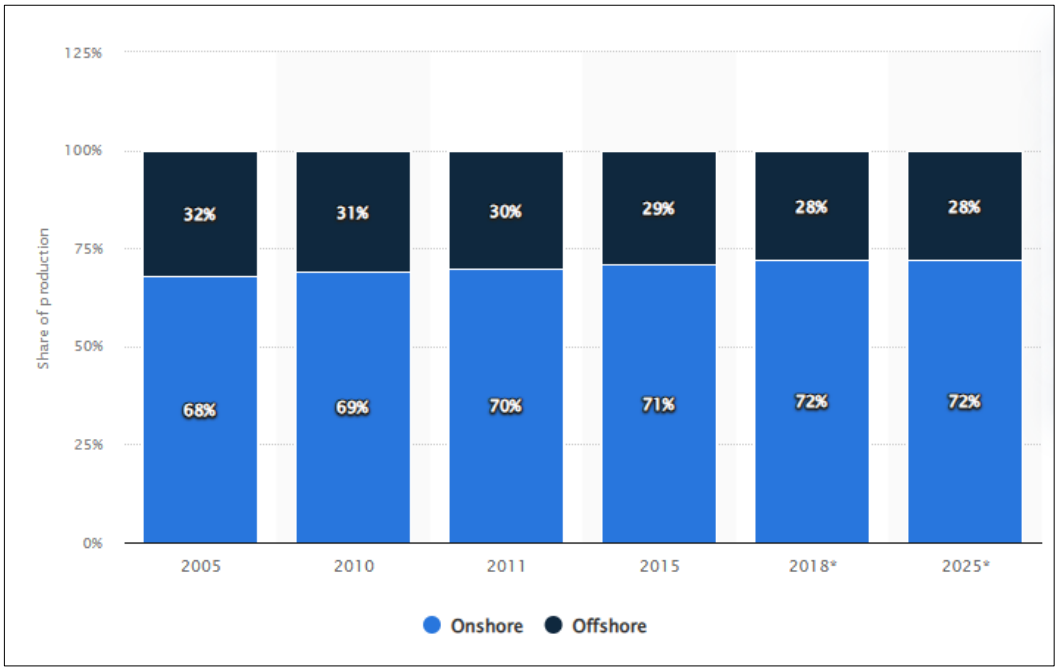


Figure 1: Distribution of onshore and offshore crude oil production worldwide from 2005--2025 (Statista, 2025)

The offshore supply chain is inherently complex, spanning both horizontal project phases and vertical stakeholder and regulatory layers. Offshore operations, from subsea drilling to topside processing and final transportation, require precision, synchronisation, and real-time adaptability (Seyyedattar et al., 2020). These challenges are further intensified by water depth, material deterioration, unpredictable reservoir performance, and changing weather conditions. Disruptions such as equipment delays, remote installation breakdowns, or vessel schedule clashes can lead to millions in daily lost production. The financial risks of offshore projects are highlighted by cases such as Australia's Gorgon LNG project, which experienced over $20 billion in cost overruns, resulting in a total of $57 billion (Meyers, 2014).

Without technological intervention, such operations are often economically unsustainable, particularly amid fluctuating energy prices and tightening margins. Offshore operations also carry significant environmental consequences, further intensifying pressure on industry actors. The Deepwater Horizon catastrophe in 2010, which released an estimated 4.9 million barrels of oil into the Gulf of Mexico, stands as a grim reminder of the sector's ecological risk (Norse & Amos, 2010). In Europe, the energy sector remains the largest emitter of greenhouse gases, accounting for approximately 27% of total emissions, as illustrated in Figure 2 below (EPA, 2022). Thus, a region's offshore energy landscape is increasingly shaped by the dual imperatives of energy security and climate action. With the EU aiming to reduce net greenhouse gas emissions by at least 55% by 2030 and achieve climate neutrality by 2050, offshore operations are being pushed to decarbonise, adopt cleaner technologies, and enhance operational transparency (EC, 2023). As such,

sustainability in offshore supply chain optimisation is no longer a peripheral objective; it is a central condition for licensing, financing, and social licences to operate.

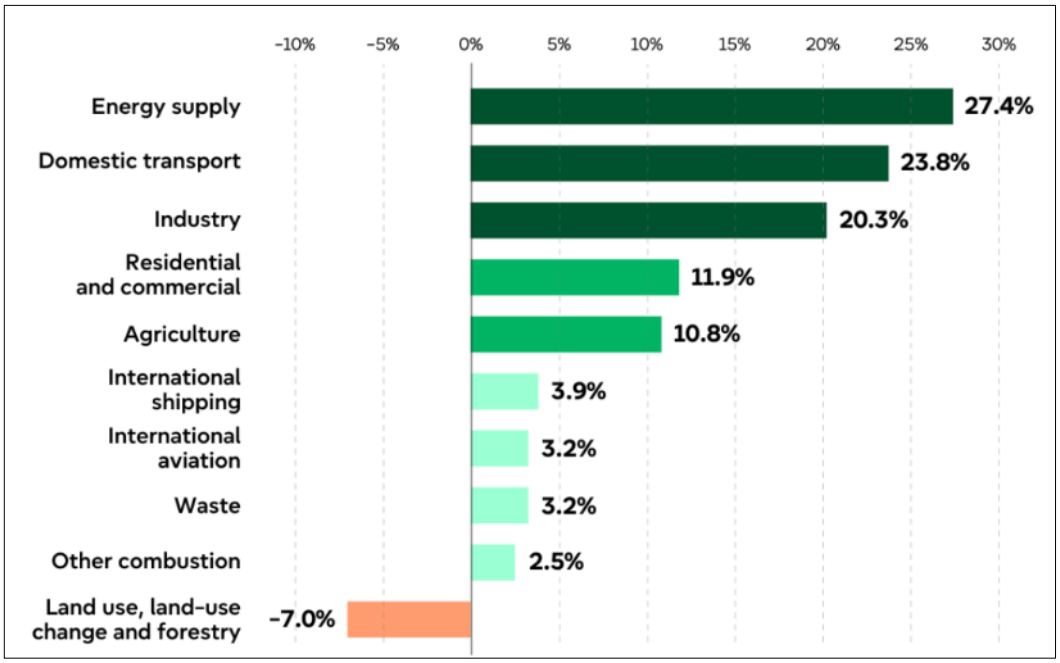


Figure 2: Greenhouse gas emissions in the EU by sector share of total emissions (EPA, 2022)

1.1 Role of artificial intelligence

In response to these converging pressures, namely, technical, economic, environmental, and geopolitical pressures, the role of digital transformation has become paramount. Artificial intelligence (AI), in particular, has emerged as a critical enabler of resilience and efficiency in offshore energy operations. AI-driven technologies such as predictive analytics, digital twins, and autonomous systems offer game-changing capabilities in monitoring, optimising, and managing risk. For example, AI algorithms can forecast equipment failures with over 90% accuracy via machine learning on sensor data, thereby preventing unplanned shutdowns (Oyeniran et al., 2023). In supply chain contexts, AI supports demand forecasting, real-time inventory tracking, dynamic routing of vessels, and adaptive scheduling, reducing costs and delays while enhancing system responsiveness (Gunasekaran & Irani, 2014). In Europe, where offshore operations span the North Sea, the Baltic Sea, and the Eastern Mediterranean, AI integration is increasingly seen as a strategic imperative for future-proofing energy systems. The application of AI in offshore asset management is also gaining traction. By deploying digital twins (virtual replicas of physical assets), engineers can simulate operational scenarios, preempt structural failures, and optimise maintenance schedules (Stroykov et al., 2021). This is particularly important for aging North Sea platforms, many of which are over three decades old and prone to structural fatigue.

Moreover, the integration of AI into offshore energy supply chains promotes not only operational resilience but also environmental sustainability. Smart monitoring systems can detect methane leaks in real time, whereas AI-enabled route optimisation reduces fuel consumption and emissions from logistics vessels. According to Adumene et al. (2023), AI enhances sustainability performance by enabling precise energy modelling, real-time emissions tracking, and eco-efficiency benchmarking, transforming offshore platforms into digitally intelligent and environmentally responsible systems. Thus, it is clear that the offshore energy sector stands at a pivotal intersection between legacy infrastructure and digital transformation. As Europe intensifies its decarbonisation

and energy security agenda amid geopolitical uncertainties and climate imperatives, the ability to operate sustainably, efficiently, and intelligently offshore is nonnegotiable. Leveraging AI for resilient supply chains and asset management is now an operational necessity and strategic advantage. This research thus aims to explore how AI is harnessed to redefine offshore energy operations in Europe, enhancing resilience, sustainability, and competitiveness in a fast-changing global energy landscape.

1.2 Overview of Offshore Energy in Europe

The offshore energy landscape in Europe encompasses two dominant domains: conventional hydrocarbon production (oil and gas) and the rapidly expanding offshore wind sector. Together, these pillars form the foundation of the region's offshore operations, underpinned by decades of infrastructure development, resource extraction, and policy-driven energy transitions. As of 2022, the European Union (EU) recorded approximately 311 active offshore installations across its maritime territories, including the Mediterranean, North Sea, Atlantic, Black Sea, and Baltic Sea regions (European Commission, 2024). A majority of these installations are legacy assets, with over 50% commissioned between 1980 and 2000, reflecting the long-standing maturity of Europe's offshore oil and gas sector. Only one new fixed installation was reported in 2022, indicating a declining trend in the development of new platforms, particularly in the North Sea and Atlantic, where activity has notably tapered since 2010 (EC, 2024).

The geographical distribution of installations reveals distinct regional patterns (see Table 1):

The **Mediterranean Sea** hosts the greatest concentration of offshore infrastructure. Italy alone accounts for 45% of all EU offshore installations, with Croatia following as a regional hub.

North Sea and Atlantic Ocean: These zones remain the most productive zones, contributing approximately 80% of the EU's domestic oil and gas output, estimated at 16,264 kilotonnes of oil equivalent (ktoe). The Netherlands and Denmark lead in production here.

Black Sea: Romania maintains a robust offshore industry, whereas Bulgaria, despite ongoing exploration, has minimal production infrastructure.

Baltic Sea: Offshore activity is limited to Poland, which maintains a modest operational presence.

This geographical and temporal fragmentation of offshore oil and gas installations underscores the need for asset repurposing, decommissioning strategies, and advanced monitoring systems—especially given the aging infrastructure and declining hydrocarbon returns (see Table 1).

In addition, the United Kingdom also hosts one of the most developed offshore oil and gas industries in Europe, primarily located on the UK Continental Shelf (UKCS), especially in the North Sea. Since the first commercial oil discovery in the late 1960s, the sector has evolved into a critical component of the UK's energy infrastructure. According to recent data, there are over 290 fixed installations and more than 80 floating production systems operating across UK waters, supporting approximately 300 active oil and gas fields (Offshore Energies UK, 2023). These installations form part of an extensive network that includes more than 12,000 km of pipelines and numerous subsea systems.

Table 1: Offshore oil and gas installations by region in 2022 (EC, 2024).

Region	**Country**	**Type of Installation (*)**					**Change compared to 2021**
		FMI	NUI	FNP	FPI	Total	
Baltic Sea	All	3	1	0	0	4	--
	Poland	3	1	0	0	4	--
Black Sea	All	5	3	0	0	8	--
	Bulgaria	0	1	0	0	1	--

	Romania	5	2	0	0	7	--
Mediterranean Sea	All	13	149	0	2	164	--
	Croatia	2	17	0	0	19	--
	Greece	1	1	0	0	2	--
	Italy	9	129	0	2	140	--
	Spain	1	2	0	0	3	--
North Sea and Atlantic	All	36	96	3	0	135	-36
	Denmark	7	11	1	0	19	--
	Germany	1	1	0	0	2	--
	Ireland	2	0	0	0	2	--
	The Netherlands	26	84	2	0	112	-36
Total		57	249	3	2	311	-36

In addition, offshore wind has emerged as a central pillar of Europe's clean energy agenda owing to the continent's vast maritime area, strong wind resources, and advanced industrial base. By mid-2024, Europe's total installed wind capacity reached 285 GW, 37 GW offshore and 248 GW onshore (WindEurope, 2025). Within the EU-27, this translated to 231 GW total, including 21 GW of offshore capacity. The pace of deployment has been encouraging. In 2024 alone, Europe installed 16.4 GW of new wind power, of which 2.6 GW came from offshore projects (WindEurope, 2025). However, this remains insufficient when juxtaposed with EU targets. The European Commission aims to reach 111 GW of offshore wind by 2030 under the Offshore Renewable Energy Strategy and scale this to 300 GW by 2050, objectives that necessitate an annual build-out of 30 GW, including 10 GW offshore per year (Reuters, 2024). To meet more ambitious climate targets (e.g., 42.5% renewable share), projections indicate the need for 33 GW per year, targeting a cumulative capacity of 425 GW by 2030. Currently, Germany, the Netherlands, Denmark, and Belgium account for the majority of installed offshore wind capacity (see Figure 3), reflecting the strategic role of the North Sea, which is expected to accommodate over 80% of Europe's future offshore wind assets. Investment trends mirror these ambitions. In 2024, WindEurope reported that Europe attracted €33 billion in new wind energy financing, catalysing 19.9 GW of additional capacity, with €18.6 billion earmarked for offshore development (Review Energy, 2025). The offshore portfolios of leading nations such as Germany (7 GW under construction), France, and the UK are significantly expanding in pursuit of decarbonisation and energy security (WindInsider, 2024).

Despite strong policy momentum and investor confidence, Europe's offshore energy ambitions, particularly in wind, still face several operational bottlenecks. Among them are grid expansion delays, slow permitting processes, and supply chain constraints, including the limited availability of specialised vessels and port infrastructure (Reuters, 2024). Notably, between 2023 and 2024, only 4.2 GW of offshore wind capacity was added (WindInsider, 2024). This value was well below the projected annual requirement, prompting urgent calls for acceleration and industrial support mechanisms.

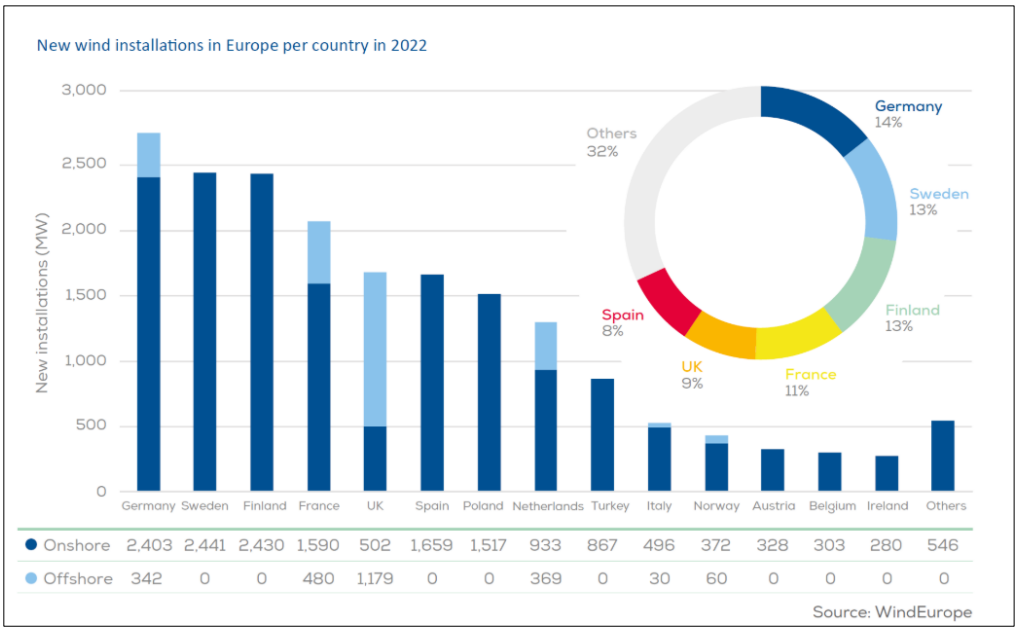


Figure 3: Offshore wind installation in Europe by country in 2022 (WindEurope, 2025)

Moreover, with the increasing complexity and scale of offshore projects, AI-driven asset management and predictive analytics are becoming essential to ensure resilience across the supply chain. Smart logistics, maintenance scheduling, and digital twins offer pathways to reduce downtime and improve forecasting for wind yield and asset performance, making digital integration as critical as hardware investment in future offshore energy systems.

2. Materials and methods

This study adopts a critical narrative review approach to examine the application of artificial intelligence (AI) in advancing sustainable offshore energy operations across Europe. This review was designed to synthesise current knowledge on AI-driven technologies, identify emerging application areas, and critically evaluate their contributions to operational efficiency, safety, environmental performance, and supply chain resilience within offshore energy systems. It integrates evidence from the academic literature with documented industrial applications to develop a comprehensive understanding of the current state of knowledge and its practical implications.

Relevant literature was identified through structured searches of major scientific databases, including Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar. Searches were conducted via combinations of keywords such as “artificial intelligence”, “machine learning”, “digital twin”, “predictive maintenance”, “offshore energy”, “offshore wind”, “offshore oil and gas”, “Internet of Things”, “autonomous systems”, “supply chain optimisation”, “offshore logistics”, “predictive analytics”, “environmental monitoring”, and “Europe”. Additional publications were identified through backwards and forward citation tracking of highly relevant studies to improve coverage of influential contributions within the field. The review primarily considered peer-reviewed journal articles published within the last decade to capture recent technological developments in AI and offshore energy systems. However, earlier seminal studies were included where they provided important theoretical foundations or remained widely recognised within the literature. To complement academic evidence, reports and technical publications from reputable organisations, including the International Energy Agency, International Renewable Energy Agency, DNV, WindEurope, the Global Wind Energy Council, and selected offshore energy companies, were incorporated where they provided verified information on industrial deployment, technology implementation, and operational performance. Such sources were used to contextualise

research findings with real-world applications while ensuring that factual claims were supported by authoritative evidence.

Following literature collection, the selected publications were examined via thematic analysis. The literature was organised into major thematic domains representing the principal applications of AI in offshore energy operations. These themes included predictive analytics and maintenance; demand forecasting; inventory management; transportation and logistics optimisation; digital twins; real-time monitoring; health, safety and environmental management; and broader sustainability implications. Within each theme, evidence from multiple studies was critically compared to identify areas of agreement, methodological differences, technological advances, implementation challenges, and emerging research directions. Rather than presenting individual studies in isolation, the review synthesises findings across the literature to develop an integrated understanding of AI-enabled offshore operations. To enhance conceptual clarity, original framework figures were developed via OpenAI's model to synthesise the relationships among AI technologies, operational processes, and sustainability outcomes discussed throughout the review.

3. AI Applications in Offshore Energy Supply Chains

Artificial intelligence (AI), particularly machine learning (ML), neural networks, and advanced analytics, underpins many transformative applications in offshore energy supply chains (Gupta & Shah, 2022).

3.1 Predictive Analytics and Maintenance

Central to AI's utility is its ability to recognise complex patterns within large operational datasets and generate reliable forecasts, making it particularly valuable for managing the technical and operational complexities of offshore energy systems. A principal application of AI in this domain is predictive maintenance, which leverages machine learning algorithms and real-time operational data to anticipate equipment failures before they occur (Erhueh et al., 2025). This capability is especially significant in offshore environments, where unscheduled maintenance activities incur substantial financial costs owing to production interruptions, specialised logistics, and limited accessibility. Consequently, predictive maintenance represents a shift from conventional time-based maintenance to condition-based asset management, enabling operators to optimise maintenance schedules while improving system reliability, asset availability, and operational safety. The literature demonstrates broad agreement that AI-driven predictive maintenance enhances operational performance by enabling early fault detection and more effective maintenance planning. For example, Equinor's implementation of AI-enabled predictive analytics at the Johan Sverdrup field in the North Sea has reportedly reduced operational downtime while improving equipment reliability, illustrating the practical value of AI within mature offshore production systems (Equinor, 2022). Likewise, Aldoseri (2024) reported that continuous analysis of sensor data can reduce downtime by up to 20% through the early identification of equipment degradation, thereby generating measurable operational cost savings. Collectively, these findings indicate that AI contributes not only to improved economic performance but also to enhanced asset integrity by facilitating timely interventions before equipment degradation progresses to critical failure.

Despite these reported benefits, the effectiveness of predictive maintenance is closely linked to the availability of high-quality operational data and the robustness of the underlying predictive models. AI algorithms rely on historical failure records and continuous sensor measurements to identify degradation patterns and forecast equipment health, making their performance sensitive to incomplete datasets, sensor inaccuracies, and evolving operating conditions. As noted by Udo et al. (2023), predictive analytics combines historical operational trends with real-time monitoring to detect anomalies and support maintenance decision-making. However, the accuracy and

transferability of these models may vary across offshore assets with different operating environments, equipment configurations, and maintenance histories, highlighting the importance of continuous model refinement and validation. Beyond improving maintenance efficiency, predictive analytics also strengthens operational decision-making by providing continuous insight into equipment conditions and enabling more informed resource allocation. The implementation of AI-based turbine vibration monitoring on Shell's Brent Bravo platform exemplifies this capability, where early fault detection reportedly prevents production losses while extending equipment service life (Accenture, 2021).

As posited by Dalzochio et al. (2020), machine learning underpins many advances in predictive maintenance by employing supervised, unsupervised, and neural network-based algorithms to classify equipment conditions, detect operational anomalies, and forecast impending failures. Unlike conventional maintenance strategies, which rely primarily on predefined inspection intervals or historical failure statistics, machine learning models continuously improve their predictive ability through exposure to new operational data, enabling maintenance decisions to evolve alongside changing equipment conditions. This adaptive learning capability is particularly valuable in offshore environments, where equipment operates under highly variable loading conditions and harsh marine environments that are often difficult to characterise via deterministic models alone (Ukato et al., 2024). The literature increasingly suggests that the value of AI-driven maintenance extends beyond improving prediction accuracy to support more efficient asset management. By identifying degradation patterns before they develop into critical failures, machine learning enables maintenance activities to be synchronised with planned operational shutdowns, thereby reducing emergency interventions, limiting production interruptions, and improving resource allocation (Ayvaz & Alpay, 2021). These operational improvements also have important safety implications, as the early identification of abnormal equipment behaviour reduces personnel exposure to hazardous maintenance activities and lowers the likelihood of incidents associated with catastrophic equipment failure. The deployment of AI-based condition monitoring systems across Ørsted's offshore wind farms in the United Kingdom, Denmark, and Germany illustrates these benefits, where continuous monitoring of gearbox and turbine performance has contributed to lower maintenance costs while improving turbine availability (Ørsted, 2023). Similarly, TotalEnergies applied machine learning at the Elgin Franklin platform in the Central North Sea to analyse pressure and temperature measurements for the early detection of hydrate formation risk, demonstrating that predictive analytics can support not only equipment reliability but also process safety and flow assurance within complex offshore gas production systems (TotalEnergies, 2021).

The growing integration of Internet of Things (IoT) technologies with AI further extends the capabilities of predictive maintenance by enabling continuous acquisition and interpretation of high-frequency operational data. IoT-enabled sensing provides a continuous stream of information that allows machine learning models to update predictions dynamically as operating conditions evolve (Nguyen et al., 2020). This integration creates a closed feedback loop in which real-time operational data continuously refine model performance while simultaneously improving the timeliness of maintenance decisions. Zaki et al. (2021) argue that this data-driven framework enhances situational awareness by providing operators with comprehensive and near real-time insights into asset health. Evidence from Equinor's Hywind Scotland floating wind project supports this view, where IoT-enabled sensing combined with AI-based performance monitoring has been used to optimise turbine operation and reduce costly maintenance interventions under challenging offshore conditions (Equinor, 2020).

3.2 Demand Forecasting

Beyond equipment monitoring, AI's predictive capabilities extend to demand forecasting, where advanced analytics support more efficient supply chain planning and resource allocation across offshore operations. AI models generate demand forecasts that are both more responsive and more adaptive than conventional forecasting approaches based primarily on historical trends by integrating market intelligence, historical consumption patterns, weather conditions, and geopolitical indicators (Onukwulu et al., 2024).

This capability is particularly valuable in offshore environments, where logistical constraints, uncertain weather conditions, and long procurement lead times amplify the operational consequences of inaccurate demand projections. Evidence from European offshore operations demonstrates the growing application of AI-enabled demand forecasting to improve supply chain resilience and operational continuity. For example, Aker BP combines AI-based forecasting with oceanographic models and shipping telemetry to coordinate offshore deliveries with favourable sea state conditions, reducing marine logistics risks while improving operational continuity in the Barents Sea (Aker BP, 2023). Similarly, BP applies AI forecasting models at the Clair Ridge field west of Shetland to anticipate production output and optimise shipping schedules, whereas Repsol employs neural network-based forecasting at its United Kingdom offshore facilities to synchronise drilling activities with supply deliveries and dynamically adjust production plans in response to supply disruptions (BP, 2020; Repsol, 2022).

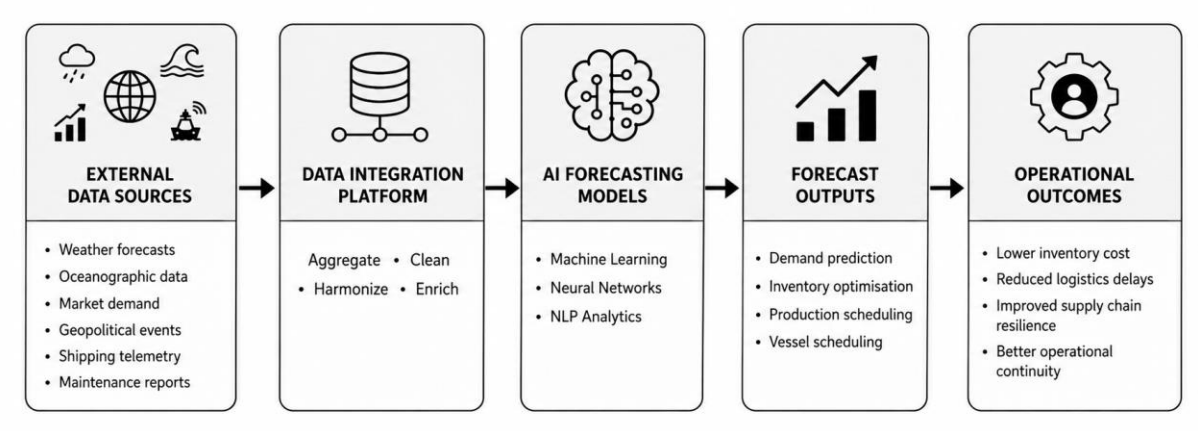


Figure. 4: AI-enabled demand forecasting framework for offshore energy supply chains (Source: Authors)

The aforementioned applications demonstrate that AI-enabled forecasting extends beyond demand estimation to facilitate integrated operational planning, where production scheduling, logistics, and inventory management are continuously coordinated via predictive insights. This integration enables operators to allocate resources more efficiently, minimise inventory imbalances, and improve responsiveness to changing operational conditions (Adewoyin et al., 2025). The interactions among the principal data sources, AI forecasting models, and operational decision-making within offshore supply chains are summarised in Figure 4 above, which illustrates how predictive analytics translates diverse operational inputs into procurement, logistics, and production planning decisions. The strategic value of AI-driven demand forecasting is further strengthened through its integration with complementary digital technologies such as natural language processing and robotics, which expand the range of operational information available for decision-making (Gupta and Sha, 2022). Natural language processing enables organisations to extract actionable insights from maintenance records, inspection reports, and operational logs that have traditionally remained underutilised, as opposed to relying solely on structured operational data. Vår Energi's application

of AI-driven natural language processing to analyse maintenance reports and offshore crew notes for adaptive inventory replenishment on the Norwegian Continental Shelf illustrates this progression from reactive inventory management towards data-driven supply chain optimisation (Vår Energi, 2023). Thus, we explore how AI enables more accurate forecasting, improved inventory control, and better alignment between offshore operational requirements and supply chain activities.

3.3 Inventory Management and Control

Within inventory management, AI is reshaping how offshore operators monitor, control, and replenish material resources by replacing static inventory practices with adaptive, data-driven decision-making. Machine learning algorithms analyse historical consumption patterns alongside real-time operational data to predict inventory requirements, enabling stock levels to be adjusted proactively rather than in response to shortages or surpluses (Hajizadeh, 2019). This represents a significant departure from conventional inventory systems, which typically rely on fixed reorder thresholds and periodic stock reviews that are less responsive to rapidly changing offshore operational conditions. Figure 5 illustrates a sample AI-enabled inventory management workflow, highlighting how real-time operational data, inventory levels, demand forecasts, and supply chain constraints are continuously integrated to support adaptive stock control and resource allocation. The workflow presented in Figure 5 complements the previous demand forecasting framework from Figure 4, emphasising that inventory management is a downstream operational application of AI.

Evidence from offshore operations indicates that AI-driven inventory management improves both inventory visibility and resource utilisation. For example, Eni has implemented AI-based inventory clustering across its offshore operations in Angola and the Mediterranean, applying unsupervised learning techniques to identify consumption patterns according to equipment type and environmental conditions. This approach has reportedly reduced supply bottlenecks while improving stock rotation, demonstrating how machine learning can enhance inventory planning through more granular analysis of operational demand (Eni, 2023). Similarly, Maersk Drilling, now part of Noble Corporation, applies AI models across North China Sea operations to optimise the drilling of consumables through intelligent restocking alerts and trend analysis, reducing the nonproductive time associated with material shortages (Maersk Drilling, 2021). Collectively, these applications illustrate that AI enables inventory decisions to be informed by continuously evolving operational conditions and not only by retrospective consumption records. Through the incorporation of contextual variables such as market conditions, operational activity, and broader supply chain disruptions, AI-based inventory systems support more adaptive and resilient inventory strategies than conventional forecasting approaches do (Barrie et al., 2024).

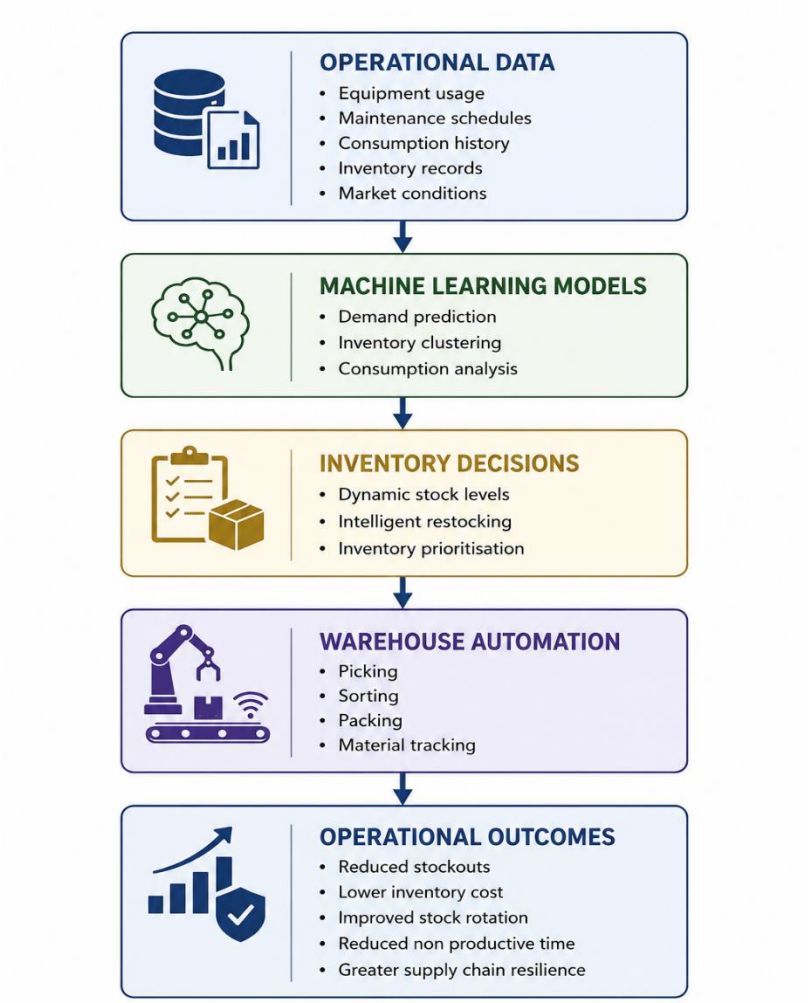


Figure. 5: AI-Driven Inventory Management and Control Architecture (Source: Author)

In addition, the application of AI to inventory management extends beyond forecasting and replenishment to the automation of warehouse operations, where intelligent systems improve both processing efficiency and inventory accuracy. Automated technologies capable of sorting, picking, and packing materials reduce manual intervention while improving the speed and consistency of inventory handling (Solanki, 2024). The combination of predictive inventory analytics with warehouse automation creates an integrated inventory management framework in which stock requirements are anticipated and replenishment decisions are continuously updated. Simultaneously, material handling processes are also optimised.

3.4 Real-Time Monitoring and Automation

Real-time monitoring has become a defining capability of modern offshore energy systems, driven by the convergence of artificial intelligence, digital twins, and autonomous technologies. Unlike conventional monitoring approaches that primarily report equipment status, these integrated digital systems provide continuous situational awareness by combining live operational data with predictive analytics and virtual asset representations (Tan et al., 2020). The result is a transition from periodic oversight to continuous operational intelligence, enabling operators to identify emerging issues, evaluate response options, and implement timely interventions before disruptions escalate. Among these technologies, digital twins have emerged as key enablers of intelligent offshore asset management. By creating virtual representations of physical infrastructures that evolve

alongside their real-world counterparts, digital twins support continuous diagnostics, operational optimisation, and scenario-based decision making (Tan et al., 2020). Their value is particularly evident in offshore environments, where harsh operating conditions and restricted accessibility limit the feasibility of frequent physical inspections. Digital twins function as dynamic decision support systems capable of integrating operational, maintenance, and logistics data into a unified analytical environment. This differs completely from serving solely as visual replicas of offshore assets. An illustration of this capability is Equinor's collaboration with KONGSBERG to develop a digital twin for a potential unmanned production platform. Built on the Kognifai platform, the system integrated real-time operational and maintenance data and projected operational expenditure savings of up to 50% alongside capital expenditure reductions approaching 30% during its initial trial phase (KONGSBERG, 2018). These gains demonstrate that the principal value of digital twins lies in their ability to support continuous operational optimisation across multiple functions.

The benefits become even more pronounced when digital twins extend beyond individual assets to represent complete offshore energy systems. System-level digital twins enable operators to evaluate installation strategies, optimise vessel mobilisation, and simulate contingency scenarios before field implementation, thereby reducing operational uncertainty and improving project execution. Qaiser et al. (2023) demonstrated this capability through the development of a comprehensive digital twin for Equinor's Hywind Tampen floating wind farm, where integrated modelling of turbine and platform energy flows indicated the potential to reduce annual carbon dioxide emissions by approximately 200,000 tonnes while improving energy delivery to the Snorre and Gullfaks fields. Similarly, Shell and Equinor applied the wellSim hiDRILL digital twin during drilling operations at the Tyttebær exploration well in the Norwegian North Sea, enabling real-time operational simulations that enhanced drilling preparedness and supported safer responses to unexpected downhole conditions (Offshore Magazine, 2018). The effectiveness of these digital environments depends on the continuous acquisition of high-quality operational data, a role increasingly fulfilled by Internet of Things technologies.

Networks of embedded sensors continuously transmit measurements such as temperature, vibration, pressure, and equipment status to AI-based analytical platforms, enabling operational conditions to be assessed as they evolve rather than after faults have occurred. This continuous feedback mechanism improves anomaly detection, supports predictive maintenance, and enables more responsive operational control. Ahmad et al. (2021) reported that organisations adopting AI-integrated IoT systems have achieved operational efficiency improvements of between 10% and 15%, highlighting the practical value of combining continuous sensing with intelligent analytics. These capabilities have also expanded opportunities for remote operations, allowing offshore facilities to be monitored and managed without continuous onsite personnel while reducing logistical complexity and operational expenditure (Solanki, 2024).

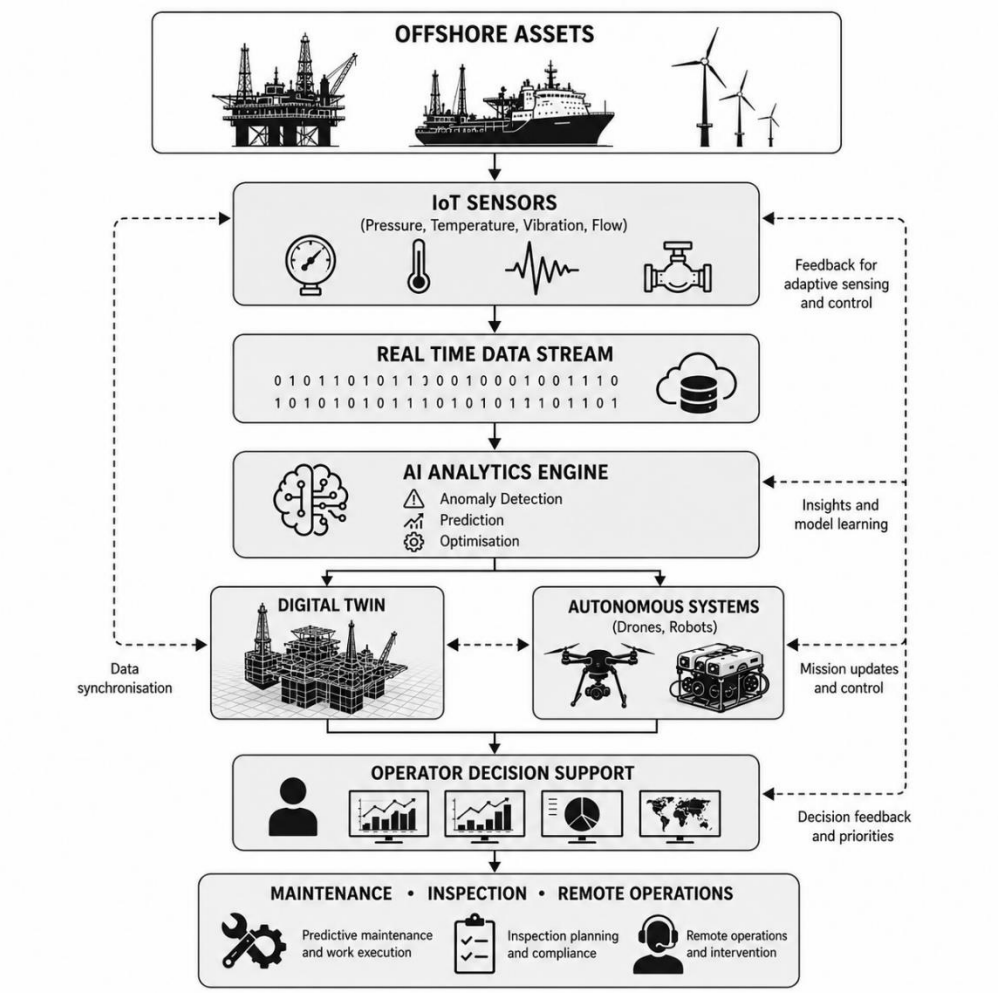


Figure. 6: Integrated intelligent offshore monitoring architecture (Source: Authors)

Such capabilities are particularly valuable in offshore settings, where adverse weather conditions and geographical isolation often constrain physical access to critical infrastructure. The integration of digital twins, IoT infrastructure, AI analytics, and remote operational control discussed above is conceptually summarised in Figure 6, which illustrates the information flow supporting intelligent offshore monitoring systems. Autonomous inspection technologies further strengthen real-time monitoring by reducing reliance on manual inspection while expanding the frequency and coverage of offshore asset surveillance. AI-enabled drones can inspect pipelines, offshore platforms, subsea structures, and terminals via high-resolution imaging and onboard sensors capable of identifying structural deterioration, corrosion, and fluid leaks at an early stage (Adeniran et al., 2024). Beyond improving inspection efficiency, these systems substantially reduce personnel exposure to hazardous offshore environments while enabling more consistent asset assessment. Compared with conventional visual inspection algorithms, the capability of these methods is further enhanced through computer vision algorithms that automate image interpretation and defect recognition, allowing anomalies to be detected with greater speed and consistency (Song et al., 2023). The integration of autonomous platforms with AI-based monitoring therefore represents more than an incremental improvement in inspection practice; it reflects a broader transition towards intelligent offshore surveillance systems in which continuous sensing, automated analysis, and remote operation collectively strengthen asset integrity, operational safety, and decision support.

3.5 Transportation and Logistics Control

Transportation and logistics represent some of the most operationally complex components of offshore energy supply chains, where vessel movements, personnel transfers, equipment deliveries, and maintenance activities must be coordinated under highly dynamic environmental conditions. In this context, AI has emerged as an important decision support technology because it enables logistics planning to evolve from static scheduling to continuous optimisation based on real-time operational intelligence. In preference to relying on predetermined routes and schedules, AI algorithms assimilate weather forecasts, vessel availability, equipment readiness, and infrastructure constraints to generate logistics plans that adapt to changing offshore conditions (Adeniran et al., 2024). The principal advantage of this adaptive capability lies in its ability to improve operational continuity while reducing logistical inefficiencies. Offshore transportation is particularly susceptible to disruptions arising from adverse weather, limited vessel availability, and narrow operational windows. AI-driven optimisation enables these uncertainties to be incorporated directly into routing and scheduling decisions, allowing operators to evaluate alternative transport strategies before disruptions affect offshore activities. By integrating meteorological forecasts with fleet status and infrastructure capacity, AI supports more efficient route selection and delivery scheduling, improving resource utilisation across offshore logistics networks (Onukwulu et al., 2023).

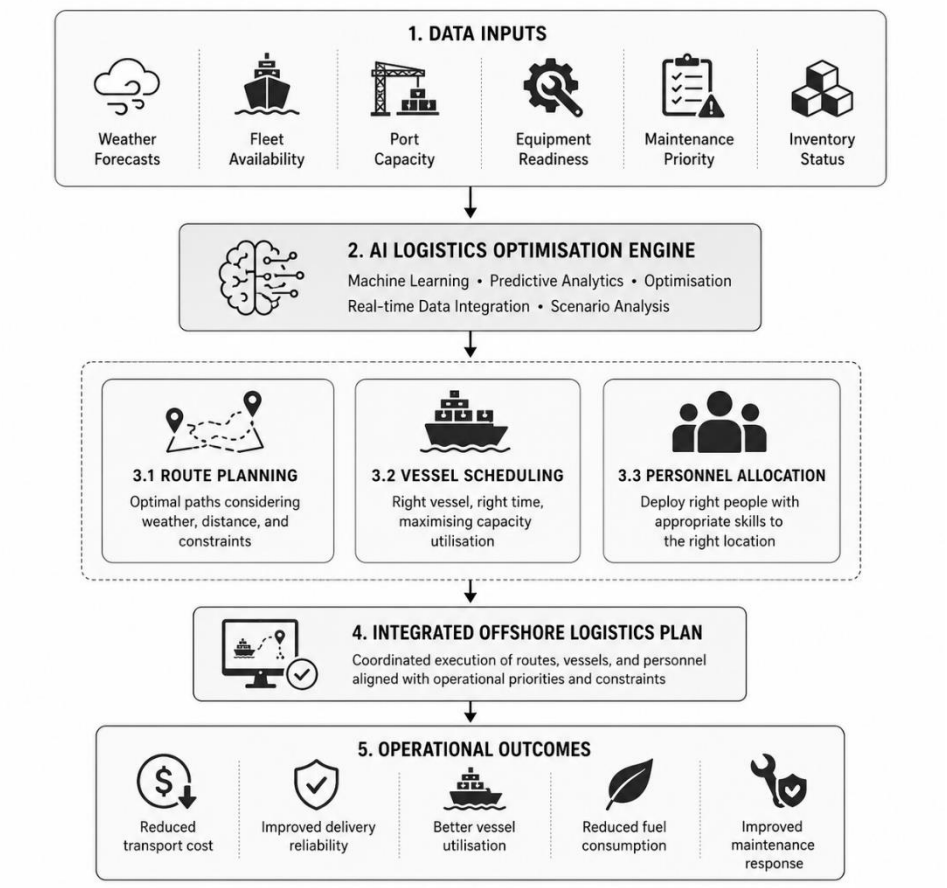


Figure. 7: AI-enabled offshore logistics framework for offshore energy supply chains (Source: Author)

Similarly, Deloitte (2024) reported that AI-enabled logistics optimisation can reduce transportation costs by up to 15% while simultaneously improving delivery reliability and reducing fuel consumption. These operational gains demonstrate that AI contributes to logistics performance not simply through route optimisation but also by enabling more responsive coordination between transportation assets and offshore operational requirements. The relationships among the principal

logistics inputs, AI optimisation processes, and operational decisions discussed above are synthesised in Figure 7, illustrating how intelligent logistics systems continuously coordinate transportation activities across offshore supply chain networks.

The value of AI-driven logistics also applies to the coordination of offshore maintenance activities, where transportation constraints frequently influence maintenance effectiveness. Mobilising specialised personnel, support vessels, and replacement components requires careful synchronisation to maximise productive time offshore while minimising unnecessary travel and resource conflicts. AI addresses this challenge by matching maintenance activities with personnel availability, competency requirements, and site accessibility, thereby improving workforce deployment under constrained operating conditions (Tan et al., 2020). This coordination is further strengthened through the integration of condition monitoring data into maintenance scheduling, allowing intervention priorities to reflect both equipment criticality and current operational requirements rather than fixed maintenance intervals (Gupta and Shah, 2022). Advanced resource allocation models extend this capability by incorporating inventory availability and the wider operational significance of individual assets into scheduling decisions, ensuring that limited logistical resources are directed towards activities with the greatest impact on system reliability (Zaki et al., 2021).

3.6 Health, Safety and Environment (HSE) Monitoring and Management

Health, safety, and environmental management remain among the most safety-critical functions within offshore energy operations, where failures can result in severe human, environmental, and economic consequences. The increasing adoption of AI reflects a broader transition from reactive risk management to continuous, intelligence-driven safety assurance. AI-enabled HSE systems integrate operational, environmental, and equipment data to provide a comprehensive view of offshore conditions, allowing emerging hazards to be identified before they develop into operational incidents (Erhueh et al., 2025). This shift is particularly valuable in offshore environments, where rapidly changing operating conditions and limited accessibility demand timely and informed decision-making. A defining characteristic of AI-based HSE systems is their ability to consolidate heterogeneous data streams into actionable operational intelligence. Information obtained from sensors, equipment diagnostics, environmental monitoring systems, and operational records can be analysed simultaneously to detect abnormal conditions that may not be apparent through conventional monitoring approaches. By continuously evaluating these interconnected datasets, AI supports dynamic risk assessment rather than periodic hazard evaluation, enabling offshore operators to intervene earlier and prioritise mitigation measures according to evolving operational conditions (Erhueh et al., 2025). Such capabilities strengthen situational awareness and improve the responsiveness of offshore safety management systems without increasing operational complexity.

The application of autonomous inspection technologies further strengthens this proactive approach to risk management. Offshore inspection activities frequently require personnel to operate in confined spaces, subsea environments, or structurally challenging locations where direct human intervention carries significant safety risks. The deployment of drones, autonomous underwater vehicles, and robotic inspection systems substantially reduces this exposure while increasing the frequency and consistency of asset inspections (John and Opeyemi, 2022). Industrial applications illustrate this progression. Equinor's Johan Sverdrup platform employs robotic inspection systems for subsea pipeline surveillance, reducing dependence on diver-based inspections while improving inspection frequency (Equinor, 2022). Similarly, autonomous underwater vehicles deployed at the Hornsea One offshore wind farm support foundation inspections under conditions where conventional inspection methods are operationally demanding (Ørsted, 2023b). In addition to replacing manual inspection activities, these systems generate high-resolution operational data that strengthen subsequent asset integrity assessments and maintenance planning. Environmental

stewardship has also benefited from the growing integration of AI within offshore operations. AI-based environmental monitoring systems continuously evaluate ecological conditions alongside operational performance, allowing environmental protection measures to become more responsive to changing site conditions. SafeWind provides an example of this ability by applying AI algorithms to monitor wildlife activity and adjust turbine operations to reduce risks to birds and bats, illustrating how ecological monitoring can be integrated into operational control systems (Zaki et al., 2021). Comparable approaches have been implemented at the Hornsea One offshore wind farm, where AI-assisted monitoring supports operational adjustments during peak seabird migration periods (Ørsted, 2023a). These developments indicate that AI increasingly supports environmental compliance through adaptive operational management rather than postevent environmental assessment, allowing offshore operators to respond more effectively to evolving ecological conditions (Ukato et al., 2024). The complementary relationships among continuous monitoring, autonomous inspection, environmental surveillance, and intelligent risk assessment are synthesised in Figure 8, illustrating the integrated AI ecosystem that underpins contemporary offshore HSE management.

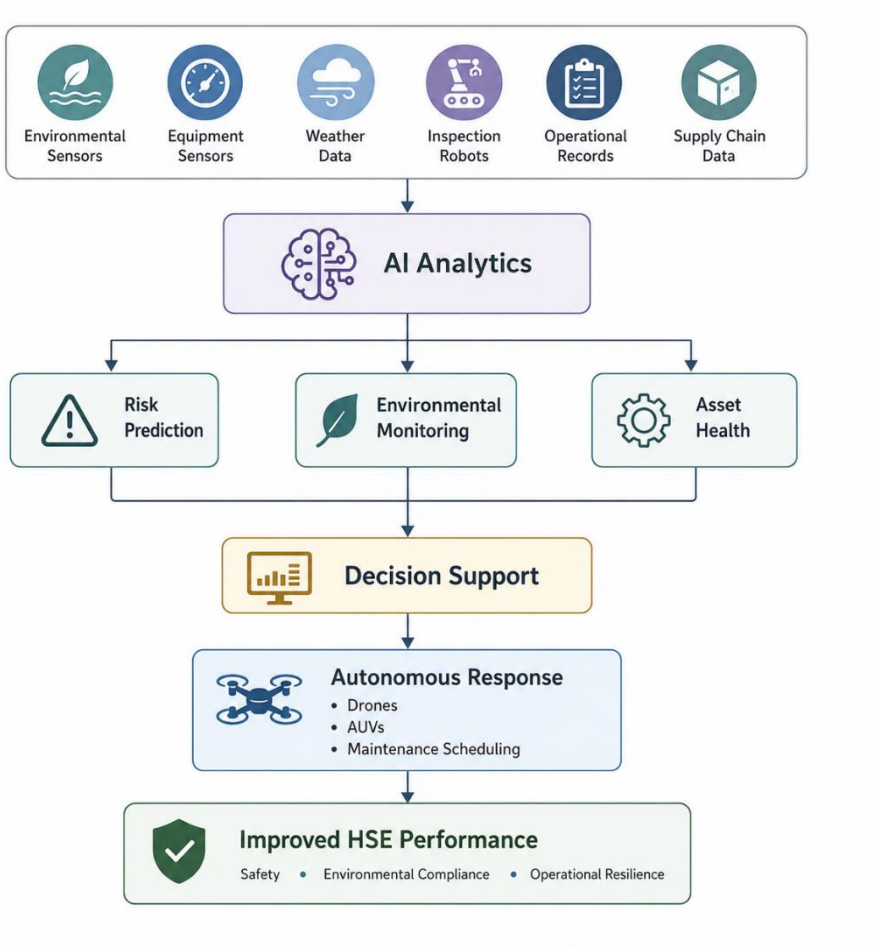


Figure 8: Integrated AI-enabled HSE Ecosystem for Offshore Operations (Source: Author)

The predictive capabilities of AI further extend the scope of HSE management by enabling offshore operators to anticipate a wider range of operational risks before they affect personnel or infrastructure. Machine learning models trained on historical operational data can identify patterns associated with equipment degradation, severe weather events, and other emerging hazards, providing additional time for preventive intervention (Arinze et al., 2024). This capability has practical importance in offshore operations, where weather-related disruptions frequently influence

operational safety and asset availability. For example, AI-enhanced weather forecasting has been adopted within the Dutch North Sea offshore sector to improve planning during severe storm conditions, increasing scheduling flexibility while reducing weather-related operational disruptions (TenneT, 2023). Similar predictive approaches have also been applied to supply chain risk management, where AI models evaluate the potential effects of geopolitical uncertainty, logistics interruptions, and market volatility on offshore operations. Applications within the Baltic Sea offshore wind sector demonstrate how predictive risk assessment can strengthen supply chain resilience and reduce the likelihood of operational disruption arising from external uncertainties (Vestas, 2024; Adewoyin et al., 2025). Real-time monitoring provides the operational mechanism through which many of these predictive capabilities are translated into timely decision-making. Continuous analysis of equipment performance, environmental conditions, and operational status enables AI systems to detect anomalies as they emerge and recommend corrective actions before failures propagate across interconnected offshore systems (Onukwulu et al., 2023). The deployment of AI-enabled monitoring platforms across North China Sea operations exemplifies this approach, where operational data from thousands of sensors are continuously analysed to support rapid responses to equipment abnormalities and environmental hazards (TotalEnergies, 2023). Rather than representing independent technological developments, predictive analytics, autonomous inspection, environmental monitoring, and real-time operational intelligence increasingly function as complementary components of integrated HSE management systems, strengthening offshore resilience through continuous risk identification, informed intervention, and adaptive operational control.

4. Conclusions

This review critically examines the growing role of artificial intelligence in advancing sustainable offshore energy operations across Europe by synthesising evidence from the offshore oil, gas, and wind sectors. The findings demonstrate that AI has evolved beyond discrete operational applications to become an integrated enabler of intelligent offshore systems, supporting predictive maintenance, demand forecasting, inventory optimisation, logistics coordination, real-time monitoring, digital twin deployment, and health, safety, and environmental management. Collectively, these capabilities strengthen operational resilience, improve asset reliability, optimise resource utilisation, and contribute to more sustainable offshore supply chains. The review further highlights that the effectiveness of AI depends not only on algorithmic capability but also on the availability of high-quality data, interoperable digital infrastructure, robust cybersecurity, skilled personnel, and supportive regulatory frameworks. Consequently, realising the full value of AI requires coordinated technological, organisational, and policy development rather than isolated digital investments.

From a practical perspective, the synthesis presented in this review provides industry stakeholders with a comprehensive understanding of how AI can be strategically integrated across offshore operations to improve efficiency while supporting Europe's decarbonisation and energy security objectives. The conceptual frameworks developed throughout the paper also provide an integrated perspective of AI-enabled offshore systems that may guide future implementation and decision-making. Future research should focus on explainable and trustworthy AI, interoperable digital ecosystems, standardised offshore data architectures, and the integration of emerging technologies such as federated learning, advanced digital twins, and autonomous decision support systems to accelerate the transition towards more resilient, intelligent, and sustainable offshore energy operations.

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resources, writing—review and editing. I.F.A.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
FMI	Fixed Manned Installation
NUI	Normally Unattended Installation
FNI	Fixed Non-Production Installation
FPI	Floating Production Installation
GW	Giga Watts
BP	British Petroleum
IoT	Internet of Things
LNG	Liquefied Natural Gas
EU	European Union
UKCS	United Kingdom Continental Shelf
HSE	Health, Safety and Environment

References

1. Accenture. (2021). AI for the real world: Shell's digital transformation of North Sea operations. Retrieved from https://www.accenture.com/gb-en/insights/energy/ai-oil-gas-shell
2. Adewoyin, M. A., Adediwin, O., & Audu, J. J. (2025). Artificial intelligence and sustainable energy development: A review of applications, challenges, and future directions. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(2), 196-203.
3. Adeniran, T. O., Bakare, F. E., & Ude, P. C. (2024). Drone technologies for pipeline and offshore infrastructure inspection in the oil and gas sector. *Journal of Energy Engineering and Technology*, 18(2), 102–115.
4. Adumene, S. A., Otunniyi, J. A., Abubakar, A. I., & Obiora, I. N. (2023). Artificial intelligence and big data analytics for sustainable oil and gas production: Current applications and future research directions. *Energy Reports*, 9, 1261–1276. https://doi.org/10.1016/j.egyr.2023.01.032
5. Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*, 289, 125834.
6. Aker BP. (2023). Harnessing AI for marine logistics optimisation. Retrieved from https://www.akerbp.com/news/ai-logistics-barents
7. Arinze, C. A., Izionworu, V. O., Isong, D., Daudu, C. D., & Adefemi, A. (2024). Integrating artificial intelligence into engineering processes for improved efficiency and safety in oil and gas operations. *Open Access Research Journal of Engineering and Technology*, 6(1), 39–51.
8. Barrie, I., Agupugo, C. P., Iguare, H. O., & Folarin, A. (2024). Leveraging machine learning to optimise renewable energy integration in developing economies. *Global Journal of Engineering and Technology Advances*, 20(03), 080–093.
9. Batra, M., Chan, S. H., & Goh, M. (2017). Logistics and supply chain challenges in the offshore oil and gas sector. *International Journal of Energy Sector Management*, 11(3), 407–422. https://doi.org/10.1108/IJESM-01-2016-0004
10. Bettley, A., & Burnley, S. (2008). Towards sustainable operations management integrating sustainability into business operations. *Management of Environmental Quality: An International Journal*, 19(5), 541–548. https://doi.org/10.1108/14777830810894259
11. Bošnjakovi´, M.; Martinovi´, M.; Đoki´, K. (2025). Application of Artificial Intelligence in Wind Power Systems. *Applied Sciences*, 15, 2443. https://doi.org/10.3390/app15052443
12. BP. (2020). Digital transformation in upstream: AI in Clair Ridge operations. Retrieved from https://www.bp.com/en/global/corporate/news-and-insights/reimagining-energy/clair-ridge-digital.html

13. Chakrabarti, S. K. (2005). Handbook of Offshore Engineering (Vols. 1–2). Elsevier.
14. Clarkston, W. G., Fontaine, D., & Power, T. (2001). Managing the complexities of offshore deepwater development. Oilfield Review, 13(2), 4–19.
15. Clean Energy Wire. (2025, February 28). European wind power capacity grows but expansion rate slightly down in 2024. https://www.cleanenergywire.org/news/european-wind-power-capacity-grows-expansion-rate-slightly down-2024
16. De Anda, M., Figueroa, R., & Trujillo, S. (2023). AI and Digital Twin Applications in Offshore Wind Turbine Logistics. *Energy Engineering Review*, 45(3), 112–126. https://doi.org/10.1016/eer.2023.07.008
17. Deloitte Insights. (2024). Power more intelligent networks: Predicting, optimising, and learning through cognitive technologies. Deloitte. https://www2.deloitte.com/us/en/insights/focus/transportation/intelligent-supply-chain-movement-of-goods.html
18. EC (2023) 2030 Climate Targets https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2030-climate-targets_en
19. Equinor. (2020). Hywind Scotland: The world's first floating wind farm. Retrieved from https://www.equinor.com/news/archive/20201008-floating-wind-hywind-scotland
20. Equinor. (2022). Robotic inspection drones enhance pipeline monitoring at Johan Sverdrup. Equinor News. Retrieved from https://www.equinor.com/en/news/2022/robotic-inspection-johan-sverdrup.html
21. Erhueh, O. V., Nwakile, C., Akano, O. A., Esiri, A. E., & Hanson, E. (2024). Digital transformation in energy asset management: Lessons for building the future of energy infrastructure. *Global Journal of Research in Science and Technology*, 2(02), 010–037.
22. Gunasekaran, A., & Irani, Z. (2014). Supply chain integration and performance: A review of the evidence. *International Journal of Production Economics*, 147, 1–2. https://doi.org/10.1016/j.ijpe.2013.08.009
23. Gupta, D., & Shah, M. (2022). A comprehensive study on artificial intelligence in oil and gas sector. *Environmental Science and Pollution Research*, 29(34), 50984–50997.
24. Hajizadeh, Y. (2019). Machine learning in oil and gas; a SWOT analysis approach. *Journal of Petroleum Science and Engineering*, 176, 661–663.
25. Harichandan, S., Behera, A. K., Panda, R., & Sahu, S. K. (2022). Offshore oil and gas industry: Recent advancements and future prospects. *Petroleum Research*, 7(4), 353–367. https://doi.org/10.1016/j.ptlrs.2022.03.006
26. International Energy Agency (IEA). (2021). Global Energy Review: CO_2 Emissions in 2021. https://www.iea.org/reports/co2-emissions-in-2021
27. International Energy Agency (IEA). (2023). Offshore Oil Production. https://www.iea.org/reports/world-energy-outlook-2023
28. John, A. O., & Oyeyemi, B. B. (2022). The Role of AI in Oil and Gas Supply Chain Optimisation
29. Maersk Drilling. (2021). Harnessing AI to improve offshore drilling efficiency. Retrieved from https://www.maerskdrilling.com/news/ai-offshore-efficiency
30. Maribus. (2014). World Ocean Review 3: The Future of Seafloor Resource Extraction. https://worldoceanreview.com/en/wor-3
31. Matos, A. C., Teixeira, A. P., & Soares, C. G. (2011). Risk analysis of complex offshore infrastructures. *Ocean Engineering*, 38(17–18), 1969–1985. https://doi.org/10.1016/j.oceaneng.2011.09.003
32. Meyers, R. (2014). *Energy: Supply and Demand*. Springer.
33. Necci, A., Tarantola, S., Cozzani, V., & Salzano, E. (2019). Quantitative assessment of domino effects caused by natural hazards in oil and gas offshore installations. *Reliability Engineering & System Safety*, 191, 106567. https://doi.org/10.1016/j.ress.2019.106567
34. Norse, E. A., & Amos, J. (2010). Impacts, perception, and policy implications of the Deepwater Horizon oil spill in the US. Marine Pollution Bulletin, 60(9), 1361–1368. https://doi.org/10.1016/j.marpolbul.2010.08.001
35. Offshore Energies UK (OEUK). (2023). UK Offshore Energy Workforce Report 2023. https://oeuk.org.uk/report/uk-offshore-energy-workforce-report-2023/
36. Onukwulu, E. C., Agho, M. O., & Eyo-Udo, N. L. (2023). Developing a framework for AI-driven optimisation of supply chains in energy sector. *Global Journal of Advanced Research and Reviews*, 1(2), 82–101.
37. Onukwulu, E. C., Agho, M. O., Eyo-Udo, N. L., Sule, A. K., & Azubuike, C. (2024). Advances in automation and AI for enhancing supply chain productivity in oil and gas. *International Journal of Research and Innovation in Applied Science*, 9(12), 654–687.
38. Oyeniran, O. K., Eke, G. A., & Ibrahim, K. O. (2023). AI-driven predictive maintenance and fault detection in oil and gas: A digital twin perspective. *Journal of Petroleum Science and Engineering*, 224, 104016. https://doi.org/10.1016/j.petrol.2022.104016
39. Ørsted. (2023a). Environmental monitoring and wildlife protection at Hornsea One offshore wind farm. Ørsted Sustainability Report 2023. Retrieved from https://orsted.com/en/sustainability/reports/2023

40. Ørsted. (2023b). Environmental monitoring and AI at Hornsea One. Retrieved from https://orsted.com/en/our-business/offshore-wind/hornsea-one
41. Rahman, M. M., & Fuad, M. M. (2018). Challenges in offshore oil and gas exploration and production: A comprehensive review. *International Journal of Petroleum and Petrochemical Engineering*, 4(1), 25–35. https://doi.org/10.20431/2454-7980.0401003
42. Repsol. (2022). AI-enabled supply chain synchronisation at North Sea platforms. Retrieved from https://www.repsol.com/en/innovation/news/ai-offshore-supply-chain
43. Review Energy. (2025, February 27). Europe installed 16.4 GW of wind energy in 2024, with Germany leading the way. Review Energy. Retrieved from https://www.review-energy.com/eolico/europe-installed-164-gw-of-wind-energy-in-2024-with-germany-leading-the-way
44. Reuters. (2024, July 21). Supply chain squeeze threatens to blow UK wind power plan off course. https://www.ft.com/content/f4ac2304-5390-4613-a7f3-6b6e57fb6e78
45. Reuters. (2024, October 24). Europe struggling to meet offshore wind targets, industry heads and lawmakers say. https://www.reuters.com/business/energy/europe-struggling-meet-offshore-wind-targets-industry-heads-lawmakers-say-2024-10-24/
46. Seyyedattar, M., Zendehboudi, S., & Butt, S. (2020). Technical and nontechnical challenges of development of offshore petroleum reservoirs: Characterisation and production. *Natural Resources Research*, 29(3), 2147-2189.
47. Solomon, B. D., & Krishna, K. (2011). The coming sustainable energy transition: History, strategies, and outlook. *Energy Policy,* 39(11), 7422–7431. https://doi.org/10.1016/j.enpol.2011.09.009
48. Solanki, A. (2024). Leveraging Data Analytics and AI to Optimise Operational Efficiency in the Oil and Gas Industry. *International Journal of Computer Trends and Technology*, 72(5), 72–81. https://doi.org/10.14445/22312803/IJCTT-V72I5P109
49. Song, Z., He, Y., & Mohammed, A. (2023). Computer vision-based inspection of offshore oil infrastructure using drones. *Ocean Engineering*, 270, 113482. https://doi.org/10.1016/j.oceaneng.2023.113482
50. Statista (2025) Distribution of onshore and offshore crude oil production worldwide from 2005 to 2025 https://www.statista.com/statistics/624138/distribution-of-crude-oil-production-worldwide-onshore-and-offshore/
    Stroykov, P., Zuev, S., & Tsvetkov, P. (2021). Digitalisation in the oil and gas industry: Transformation of asset management. *Energies*, 14(7), 1951. https://doi.org/10.3390/en14071951
51. Tan, J.H., Roberts, B., Sundararaju, P., Sintive, C., Facheris, L., Vanden Bosch, J., Lehning, V. and Pegg, M. (2020, October). Transforming offshore oil and gas production platforms into smart unmanned installations. *In Offshore Technology Conference Asia* (p. D031S026R001). OTC.
52. TenneT. (2023). AI-driven weather forecasting improves offshore operations in the Dutch North Sea. TenneT Innovation Insights. Retrieved from https://www.tennet.eu/newsroom/2023/ai-weather-forecasting
53. TotalEnergies. (2021). AI transforms flow assurance at Elgin-Franklin. Retrieved from https://totalenergies.com/media/news/ai-elgin-franklin
54. TotalEnergies. (2022). Drones and AI transforming inventory management. Retrieved from https://totalenergies.com/newsroom/news/ai-inventory-drones
55. TotalEnergies. (2023). Smart monitoring hubs enhance safety on North Sea oil platforms. TotalEnergies Annual Report. Retrieved from https://totalenergies.com/safety-innovation/north-sea-platforms-2023
56. Ukato, A., Sofoluwe, O. O., Jambol, D. D., & Ochulor, O. J. (2024). Optimising maintenance logistics on offshore platforms with AI: Current strategies and future innovations. *World Journal of Advanced Research and Reviews*, 22(1), 1920–1929.
57. Vår Energi. (2023). AI-driven procurement signal extraction in offshore energy. Retrieved from https://varenergi.no/news/ai-nlp-inventory-forecasting
58. Vestas. (2024). Supply chain resilience through AI in Baltic Sea offshore wind projects. Vestas Corporate Reports. Retrieved from https://www.vestas.com/en/sustainability/supply-chain
59. WindEurope. (2025, February 27). Wind Europe Statistics: Europe Installed 16.4 GW of New Wind Energy Capacity in 2024. WindInsider. Retrieved from https://windinsider.com/2025/02/27/windeurope-europe-added-16-4-gw-of-new-wind-energy-capacity-in-2024/
60. WindEurope. (2025, March 4). Wind energy in Europe: 2024 Statistics and the outlook for 2025–2030. WindIndustry in Germany & Windfair.
61. WindInsider. (2025, February 28). WindEurope's Autumn Wind Energy Data: Europe Adds 6.4 GW of Wind Capacity in 2024 but faces grid and investment hurdles. https://windinsider.com/2024/09/18/windeuropes-autumn-report-europe-adds-6-4-gw-of-wind-capacity-in-2024-but-faces-grid-and-investment-hurdles/

62. Zaki, O., Dunnigan, M., Robu, V. and Flynn, D. (2021). Reliability and safety of autonomous systems based on semantic modelling for self-certification. *Robotics*, 10(1), 10.

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