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ARTICLE

# Remote Intelligence at Sea: Enabling Smart Vessel Operations through AI-Driven Monitoring and Control

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ABSTRACT

The maritime industry is undergoing a technological transformation driven by the integration of artificial intelligence (AI) into shipboard operations. This article discusses the topic of remote intelligence in the ocean, which implies the use of AI applications on a ship to receive autonomous control over the shipboard conditions, failure forecasting, and regulation of critical operations. Through machine learning, sensor data, and edge computing, smart vessels will need less support on the shore, and will be able to increase their efficiency, safety, and resilience of their operations. Using secondary sources of data and documented case studies, the study analyses the functionality of AI in maritime environments such as condition monitoring, predictive maintenance, energy optimization, and autonomous navigation. It also reveals the major challenges, including restriction of technology, cybersecurity threat, absence of regulations and organizational resistance. The paper ends on the note that the industry will have to work together, that regulation must be innovated, and people and AI must fuse to get the most out of intelligent vessel operation.

## 1. Introduction

The shipping sector has a history of being the main sector of global trade as it aids more than 80 per cent of the trade by a measure of tonnage. This massive responsibility is associated with the increased need for improved efficiency of operations, better safety, and lower impact on the environment. Historically, the maritime sector has been very dependent on human expertise, whether at a position on the boat or in the control centre,

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manned land-based. The crews of ships are obliged to check a huge range of mechanical, navigational and weather conditions when they may have to work under stressful and unforeseeable conditions. However, despite the development of communication technologies, a significant reliance on human interpretation ability and shore support is still observed, which causes delays, ineffectiveness, and vulnerability in critical situations like equipment breakdown or bad weather [1,2].

The maritime sector has recently started to transform due to digitalisation, and an essential contributor to the intelligent operation of a vessel is artificial intelligence (AI). AI technologies provide a paradigm shift from reactive and human-to-human decision-making to active, autonomic and data-driven operations. The integration of AI with next-generation sensor technologies, real-time data analytics, and edge computing capabilities has not only resulted in the creation of so-called smart ships; vessels that are designed to process and analyze data to identify anomalies, forecast failures or even automatically make independent decisions, with no need of constant human data monitoring. The integration enables the vessels to work more securely, efficiently, and with less ecological effect, as well as decreasing the working load on the craftsmen and personnel on land [3].

The present research paper outlines the issue of Remote Intelligence at Sea, which is the ability of ships to automatically observe, process, and respond to the dynamics of the operation in the form of AI-powered systems that are internally installed. In contrast to the previous automation models that necessitated a sustained connection to centralized structures, remote intelligence is also preoccupied with the prospect of allowing a vessel itself to be a semi-autonomous or autonomous organism, able to make local decisions in real time. This ability is especially beneficial in long oceanic flights, where a lack of communication and connection bottlenecks may put a damper on prompt human control. Remote intelligence, therefore, boosts the operating viability of a vessel and reduces unplanned downtimes, turnaround times, and ensures safer operations at sea [4].

Technological advances in machine learning, computer vision, predictive analytics and cyber-physical systems have spurred the interest of the maritime industry in AI. These technologies have been applied in a number of important functions, including maintenance, live characterisation of engine performance, fuel proficiency, auto-route preplanning, and self-governing navigation. Industry players like Rolls-Royce, Wartsila, and ABB, industry partnership organisations like One Sea and classification companies like DNV and Lloyds Register have begun projects and pilot programmes to integrate AI into shipboard systems. The activities will result in the development of vessels that can autonomously perform most of the usual operations and be adaptive to the sudden changes of the situation of work [5].

Regardless of the raised interest, one may still meet the significant gap in the comprehension of the overall implications and possibilities of AI systems embedded in the vessels. Most of the existing literature is inclined to concentrate on technical feasibility, hardware systems or even individual functionalities (like navigation or propulsion). However, the present paper is more systems-thinking oriented on the way onboard AI can be used in end-to-end vessel operation by monitoring and control in real-time. This will introduce a conceptual and pragmatic ability that allows remote intelligence, as facilitated by an embedded AI, to change the nature of maritime activities, efficiency, and the necessity to rely on constant shore-based assistance [6].

More importantly, the gathering of new primary data or surveys is not used in this paper. Rather, it rests upon the in-depth analysis of the secondary sources such as the academic literature, technical reports, statutory materials, and published cases. The method provides the opportunity to combine the available information and review the experiences of real-life applications of AI-driven systems at sea. Since it dwells on documented experiences, as well as verified case examples, this paper points out the opportunities and the challenges of deploying AI to make autonomous operations possible on a shipboard [7].

The rest of the paper is organised into four sections, with the most important. Section 2 depicts the conceptual view that underpins AI-based vessel intelligence, which defines the technological aspects and operational system that create the possibility of onboard autonomy. Section 3 is an investigation of the variety of functions that AI may maintain, starting with condition monitoring and predictive maintenance and proceeding through to autonomous control and route optimisation. Section 4 takes a bold look at both the technical, regulatory and organizational issues that need to be resolved in safely and successfully deploying these technologies safely and successfully. Lastly, Section 5 ends by looking at the implications of the findings for the maritime sector and future studies.

The fade of the less digitized and autonomous industry to the more digitized and autonomous version makes the explanation of the role of remote intelligence on the seas more relevant and probable. This study adds to an increasing body of knowledge that helps to transform the global maritime business in a safe, efficient and sustainable way through the intelligent monitoring and control enabled by AI embedded systems on vessels [8,9].

## 2. Conceptual Framework: AI-Driven Vessel Intelligence

The theory of remote intelligence on the sea is embedded in a wider background of intelligent systems that permit autonomous or semi-autonomous decision-making within a complicated, changing world. To the vessels deployed to an uncertain marine environment, the integration of Artificial Intelligence (AI) technologies aboard constitutes a radical change in managing the ship in, real-time, resilient, and efficient manner. The section will explain the major constituents, operational architecture and data paradigms that represent AI-driven vessel intelligence as a whole [10].

### 2.1 Defining Remote Intelligence in Maritime Context

Remote intelligence can be defined as the ability of a ship through the AI-based systems placed on board it to observe, interpret, and react to the operational environment autonomously and without the external input required in real-time. It is specific as it is characterised by:

- **Self-monitoring** of shipboard systems (e.g., engines, power, navigation).
- **Predictive and diagnostic abilities**, enabling foresight into equipment behaviour.
- **Autonomous control actions**, where AI systems can adjust operations in response to anomalies or optimisation triggers.

This is an extension of conventional automation, which generally implies predetermined rules or reactive sensors, by presenting adaptive learning and decision algorithms that could make generalisations based on a history of information in order to make sense of fresh circumstances.

### 2.2 Core Components of Vessel Intelligence

An AI-driven smart vessel typically includes the following technical elements:

**a. Sensor Ecosystem**

A network of onboard sensors collects continuous data on engine performance, vibration, temperature, humidity, hull stress, fuel consumption, weather conditions, and navigational data. These sensors form the foundational layer of the vessel's situational awareness.

**b. Edge Computing Units**

Rather than transmitting all raw data to shore, edge computing systems process data onboard. These systems run AI models locally to ensure:

- **Low latency** responses.
- **Autonomy during low-connectivity periods**.
- **Bandwidth-efficient operations**.

Edge AI is especially vital in marine environments where satellite communication can be limited, costly, or delayed.

**c. AI Algorithms and Models**

AI models embedded on vessels include:

- **Machine Learning (ML)** for pattern recognition and anomaly detection.
- **Neural Networks** for adaptive diagnostics.
- **Reinforcement Learning** for control optimisation.
- **Computer Vision** for surveillance, obstacle detection, and situational recognition (e.g., automated watchkeeping systems).

These models are trained using historical datasets and refined with operational data from live voyages.

**d. Cyber-Physical Systems (CPS)**

Smart vessels represent a maritime implementation of CPS systems where digital intelligence is tightly integrated with physical processes. AI interacts with onboard control systems (e.g., propulsion, ballast systems) to take corrective actions, trigger alerts, or adjust settings autonomously.

**e. Human-Machine Interface (HMI)**

Although the aim is autonomy, humans remain an essential part of the loop. Advanced interfaces provide the crew with AI-generated insights, diagnostics, and recommended actions. These systems must be interpretable, providing explainable AI outputs that support trust and safe intervention when needed [11-13].

### 2.3 Operational Architecture of Smart Ship Systems

The operational flow of AI-driven vessel intelligence can be visualised across three layers:

**1. Perception Layer**

- o Data acquisition from sensors, radars, cameras, and control systems.
- o Pre-processing of raw data for quality, consistency, and integration.

**2. Decision Layer**

- o Execution of AI/ML models for prediction, classification, and optimisation.
- o Fusion of different data streams (e.g., engine + weather data) to create holistic insights.

**3. Action Layer**

- o Real-time feedback into ship systems.
- o Initiation of control commands (e.g., throttle adjustment, steering correction).
- o Generation of alerts or reports for the crew or

shore teams when necessary.

This layered architecture supports both reactive and proactive actions, with learning loops that allow models to continuously improve through exposure to operational data [14].

### 2.4 The Role of Secondary Data in AI Model Development

Since this paper relies solely on secondary data sources, it is important to recognise how AI systems on vessels are typically trained and validated using existing datasets such as:

- **Operational logs** from shipping companies.
- **Maintenance and failure records** from classification societies.
- **Weather and oceanographic data** from open-source repositories (e.g., NOAA, ECMWF).
- **Case studies** and technical reports from AI vendors and maritime technology providers.

These secondary datasets enable supervised and unsupervised learning approaches, helping to identify performance baselines, detect deviation patterns, and simulate various risk scenarios.

Importantly, publicly available datasets and published case examples (such as those involving Wärtsilä's Smart Marine Ecosystem or the Yara Birkeland autonomous container ship) offer a solid foundation for building AI frameworks without the need for proprietary primary data collection [15].

### 2.5 Digital Twins and Simulation for Model Validation

Digital twins—virtual replicas of real-world vessels—are often used in tandem with AI to simulate performance, test scenarios, and validate model behaviour before deployment. These simulations use archived sensor data and historical voyage records to replicate vessel responses to a range of operating conditions, making them essential tools in the AI deployment lifecycle.

By relying on simulations and historical data, developers can ensure safety, reliability, and regulatory compliance without introducing risks to live operations.

### 2.6 Benefits of an AI-Embedded Architecture

Implementing an AI-embedded ship architecture has significant implications:

- Reduced dependence on shore-based control centres.
- Faster response times in case of system anomalies.
- Enhanced voyage efficiency and environmental performance.
- Lower long-term maintenance costs through predictive insights.
- Improved crew safety through automated alert systems and risk prediction.

Briefly, AI applied to the intelligence of vessel intelligence can be made possible through a confluence of sensors, compulsory processing, machine learning models, and real-time control systems. This framework provides a transition between the idea of centralised and reactive decision-making to the model of decentralised and proactive decision-making in which the vessel is an intelligent agent. In the next section, we examine how the capabilities are in the process of being put in applications in the real world to handle and optimise ship functions autonomously [16].

## 3. Functional Capabilities Enabled by Onboard AI

Artificial intelligence (AI) integration on the shipboard does not imply a mere improvement of maritime technology; the approach constitutes a game changer in the manner in which ships operate, react and manage their operations in real-time. Smart systems are leading to the ability of vessels to undertake various tasks during operations either autonomously or with some degree of autonomy, leading to developments in reliability, eliminating the chances of human error and overall efficiency. The current section provides an exploration of the main functional potentials offered by embedded AI technologies on the sea, which is facilitated by the industry case studies and secondary sources [17].

### 3.1 Autonomous Condition Monitoring

Among the applications of onboard AI, autonomous condition monitoring must be considered one of the most important since it entails the capability to constantly monitor and analyse the operating condition of major ship systems and parts without the direct involvement of humans in the process.

**Key Features:**

- Monitoring of engines, pumps, hull stress, fuel systems, emissions, and navigational equipment.
- Use of pattern recognition algorithms to detect operational deviations in real time.
- Alert generation based on anomalies or threshold breaches.

**Industry Example:**

Rolls-Royce engineers have created smart engines monitoring systems, which incorporate AI to interpret thousands of data acquired by the second through engine sensors. Such systems detect abnormalities, including strange vibrations or temperature deviations, which allows detecting wear and tear early.

The Fleet Operations Solution (FOS) developed by Wartsil has combined condition monitoring and route optimization, and weather analysis by introducing AI to help crews to make sound choices about how the vessel performs [18].

### 3.2 Predictive Maintenance and Fault Prevention

The most commercial potential of AI applications in maritime activities is predictive maintenance. On models, AI can predict component aircraft failure on historical data and current operating conditions to enable the maintenance team to interfere before the failure normally happens.

**Key Features:**

- Predictive models trained on failure modes, root causes, and degradation patterns.
- Estimation of Remaining Useful Life (RUL) for key machinery.
- Maintenance schedules are optimized based on actual condition rather than fixed intervals.

**Industry Example:**

ABB's **Ability™ Marine Advisory System** is an AI-based platform that uses predictive diagnostics to determine when specific parts of shipboard systems are likely to fail. This prevents costly unscheduled downtime and enables condition-based maintenance.

Maersk, in conjunction with analytics companies, has implemented machine learning models in a bid to identify possible breakdowns in the fuel system, a fleet-wide application based on more than 10 years of historical data of maintenance [19].

### 3.3 Energy Efficiency and Fuel Optimization

AI solutions also find more use in fuel efficiency and energy optimisation, which cover economic and environmental ambitions.

**Key Features:**

- Adaptive engine tuning and throttle optimization.
- Real-time adjustments to reduce drag, trim, and speed-related fuel consumption.
- Integration with weather and sea-state forecasting for optimal voyage planning.

**Industry Example:**

The Yara Birkeland, the first container ship in the world, powered by electricity with the help of AI algorithms, is a ship that minimizes its energy consumption during every journey. Its propulsion system and battery are actively controlled about operational requirements and weather scenarios. In a further application, Shell has worked with predictive analytics companies in order to apply AI-powered fuel optimization to its fleet, saving itself millions in fuel expenditures yearly by optimizing fleet workings via machine learning [20].

### 3.4 AI-Assisted Navigation and Collision Avoidance

The use of AI in autonomous navigation is great, especially when the environment is congested or risky. The systems can assess the traffic, anticipate vessel movement and prescribe or carry out evasive manoeuvres.

**Key Features:**

- Integration with AIS, radar, GPS, and visual inputs.
- Computer vision for detecting other vessels, buoys, and obstacles.
- Dynamic re-routing based on risk prediction and environmental factors.

**Industry Example:**

The **Sea Machines SM300** system enables remote and autonomous control of vessels using AI-powered navigation software. It includes object recognition, obstacle avoidance, and remote situational awareness, allowing for automated patrol or survey missions.

Japan's **NYK Line** has trialled AI-based navigation systems that predict collision risks and propose optimal navigational paths, demonstrating reduced decision time and improved safety margins in simulations [21].

### 3.5 Integrated Decision Support Systems

In addition to the specific functions, AI is also prominent in decision support, whereby synergized complex data flows are used to support both human decisions and autonomous decisions.

Key Features:

- Combination of sensor data, weather predictions, traffic data and past performance.
- Predictive dashboards that may include recommended actions in real-time.
- Reports based on AI that will be made by shore-based operations centres of fleets.

Industry Example:

Veracity, a platform developed by DNV, should enable shipowners to gain AI-based understanding of their fleet performance, environmental performance, and routes. The system compiles data available onboard. It uses analytics models and provides recommendations that are actionable.

Likewise, One Sea Alliance, which is an effort between maritime technology companies, has advocated integrated decision systems of autonomous vessels, where AI weighs inputs on propulsion, logistics, and weather in order to continue performing optimally [22].

### 3.6 Emergency Response and Risk Mitigation

It is also now using AI systems in aid of the emergency response situation, like fire on board, engine failure, or piracy threats. Such systems can:

- Detect hazardous patterns early.
- Trigger alerts and recommended protocols.
- Interface with control systems to initiate safe shutdowns or evasive actions.

Although in early stages, AI's role in **risk mitigation** is expected to expand significantly with the maturity of autonomous shipping standards.

### 3.7 Summary of Functional Benefits

Overviewing, the vessels equipped with AI-embedded systems are being provided with a set of working capabilities, making them very operational autonomously and resistant. Such systems do not operate in the place of human operators but augment their capabilities such that they offer real-time insights, decrease reaction times, and allow optimisation in performance that would be hard or not at all possible to attain through a human operator. The third chapter will critically target the technical, regulatory, and human factors, presenting technical and regulatory (as well as human) challenges to the widespread application of these AI-driven maritime systems [23].

| Functional Area | Key AI-Driven Benefits |
|---|---|
| Condition Monitoring | Real-time fault detection, reduced downtime. |
| Predictive Maintenance | Lower repair costs, fewer unscheduled outages |
| Fuel and Route Optimization | Fuel savings, reduced emissions |
| Navigation and Safety | Enhanced situational awareness, fewer accidents |
| Decision Support | Faster, more informed operational decisions |
| Emergency Response | Early risk identification, faster mitigation |

## 4. Risks and Issues

Although introducing artificial intelligence (AI) on shipboard is associated with high opportunities in terms of operation, economics, and environmental safety, it is accompanied by a whole range of technical, regulatory, organization, and ethical issues. With all the interconnected benefits to the industry, the means of achieving the full-scale adoption of remote intelligence at sea is quite complicated and will involve coordinating the efforts of shipowners, technology providers, regulators, classification societies, and seafarers. In this section, the primary challenges and considerations that should be made to ensure that it is possible to guarantee safe, reliable, and scalable deployment of AI-driven vessel operations are also critically discussed.

### 4.1 Infrastructure constraints and technological shortages

Although the technology around AI is developing very fast, quite several constraints on technology exist as far as its application in marine environments is concerned:

**a. Data Quality and Goodness of Sensors**

The quality, consistency and granularity of sensor data are essential to the performance of AI models.

- Marine locations are potentially harsh environments that are very humid, highly salty, and they are subject to vibration that may result in poor accuracy in sensing, or give incomplete data.

Irregular data streams or failed sensor data can result in incorrect conclusions, non-existent alarms or missed anomalies.

**b. Quickly Consumable Computing Resources Aboard**

- AI models become complicated to run in real-time, with considerable performance (intense learning).
- In many of the current vessels, the hardware capacity or bandwidth is not there to make high-performance processing on board.

The process of retrofitting old vessels is usually expensive and technically demanding.

**c. Model Explainability and Credibility**

- Most models of AI, and particularly neural networks, are black box models that generate outcomes without explanations.
- Safety-critical systems are prone to model transparency, which impedes decisions and destroys trust in the operators.

There is an increasing demand for explainable AI (XAI) methods where the outputs can be explained and verified [24].

### 4.2 Concerns on Safety, Security and Ethics

The process of replacing people with AI-based vessel operations creates considerable safety and cybersecurity risks:

**a. Safety Guarantee and Fail-Safes**

- Autonomous systems have to be hard-tested in all conditions of their operation that are possible to determine.

It is necessary to have redundancy and fail-safe capabilities to accommodate out-of-order events (e.g., software bugs, incompatible sensor indications).

- The use of AI decisions on commercial roads needs to be audited on safety before being used.

**b. Cybersecurity Risks**

- Increasingly, smart vessels that are interconnected are at risk of a navigation, propulsion, or cargo hack, posing a cyber threat.
- Algorithms themselves can be susceptible to adversarial attacks: they can be poisoned with labelled data, or a signal can be spoofed.
- Cybersecurity standards in the maritime industry (e.g. IMO 2021) are constantly changing, but fall behind in the pace of AI development.

**c. Moral (Ethical and Legal Implications)**

However, some questions about accountability emerge: Who is to blame when the shipowner is affected by an autonomous system, the unfortunate shipowner, the AI vendor or the crew?

Ethical issues relate to the possibility of causing job displacement, access disparity to technology, and unwanted bias to AI models trained on small amounts of data [25,26].

## 4.3 Regulatory and Standardization Barriers

The maritime industry operates under a complex web of international and national regulations, most of which were designed for human-operated vessels. AI and autonomy challenge the applicability of these frameworks:

**a. Lack of Clear Guidelines**

- There are currently no unified global standards for the design, testing, or certification of AI-driven vessel systems.
- Regulatory ambiguity creates uncertainty for shipowners and technology developers.

**b. Lag in Regulatory Adaptation**

- The International Maritime Organization (IMO) has initiated discussions on **Maritime Autonomous Surface Ships (MASS)**, but progress is slow.
- Classification societies such as DNV, ABS, and Lloyd's Register have begun issuing AI and autonomy notations, yet there is no harmonized regulatory baseline.

**c. Port and Coastal State Readiness**

- Even if vessels become AI-enabled, many ports and coastal states are unprepared to handle or regulate autonomous arrivals.
- Coordination between flag states, port authorities, and shipping companies is essential to enable real-world deployment.

## 4.4 Organizational and Operational Resistance

AI systems demand not only new technologies but also a transformation in operational culture and workforce readiness.

**a. Crew Training and Digital Skills Gap**

- Many seafarers lack the training to understand, operate, or troubleshoot AI-based systems.
- Without upskilling programs, there is a risk of misusing or distrusting these systems.

**b. Resistance to Organizational Change**

- Traditional maritime culture often emphasizes human judgment and manual control.
- Organisational inertia, particularly in conservative or cost-sensitive shipping companies, can delay AI adoption.

**c. Fragmented Technology Ecosystem**

- Multiple vendors offer proprietary AI systems with limited interoperability.
- A lack of open standards complicates system integration and data exchange between ships, ports, and fleet management centres [28].

## 4.5 Financial and Economic Constraints

Implementing AI-driven systems is capital-intensive, especially when retrofitting existing vessels.

- The **high cost** of advanced sensors, edge computing units, software licenses, and cybersecurity tools can deter small and mid-sized operators.
- **Unclear return on investment (ROI)** due to uncertain fuel savings, regulatory delays, or insurance impacts may delay adoption.
- Without robust economic incentives (e.g., tax credits, green shipping subsidies), the business case for full autonomy remains limited for many operators.

## 4.6 Human-AI Collaboration Challenges

Instead of an all-human-replacing design, most current designs of smart vessels focus on augmented intelligence, which means that AI will aid the crew instead of replacing it.

- Effective performance of human and AI collaboration is achieved when the interface is designed with care, proper distribution of work, and tolerance to errors.
- Crew members should have trust in AI outputs, but at the same time feel free to take over AI when

necessary.

- Putting trust in the wrong place, e.g. too much or too little, may make the system less effective or present more risks to its operations [29].

**Summary Table: Key Challenges**

| Challenge Category | Specific Issues |
|---|---|
| Technological | Sensor reliability, edge computing limits, and model transparency |
| Safety & Security | Cyber threats, fail-safes, and ethical responsibility |
| Regulatory | Lack of standards, IMO MASS gaps, and port readiness |
| Organizational | Skills gap, cultural resistance, vendor fragmentation |
| Economic | High costs, ROI uncertainty, and retrofit barriers |
| Human Factors | Trust calibration, interface design, and shared decision-making. |

Overall, in summary, although AI-enabled vessel intelligence could be taken as a potentially transformative technology when used in maritime operations, its implementation does not come without great difficulties. These world impediments will have to be defeated through a multi-stakeholder approach that will strike a balance between innovation with safety, and technology with the skills of human experts. In our conclusion, we draw some essential conclusions and outline the directions in which the maritime industry should move to “embrace” remote intelligence in a responsible manner at sea

## 5. Conclusion

As the shipping sector undergoes the challenges of globalization, environment-friendliness and efficient operations, artificial intelligence (AI) use is no longer a growing technology but a strategic requirement. This essay has discussed how the idea of remote intelligence in the sea, making use of embedded AI software, could end up transforming the operations of vessels, including their lack of necessity to rely on the shore infrastructure perpetually to monitor, forecast and manage essential functions automatically. With the help of a review of secondary data sources and outlined case studies, we studied the theoretical framework of the architecture of smart vessels, the major functionalities that AI-driven systems can achieve predictive maintenance, autonomous navigation, and real-time condition monitoring of vessels, and discussed the operational advantages of these capabilities. It is important to note that AI onboard enables vessels to transform into adaptive, proactive, and resilient body - in-abilities to respond to dynamic marine conditions that would contribute to safety, efficiency, and sustainability. But there is much trash on the path to achieving these benefits. Technological deficiencies, including sensor-reliability and computing-constraints, should be overcome to guarantee proper and on-time decision-making in situ. Of equal concern are the issues about safety, cybersecurity, and ethics that arise whenever management is entrusted to smart systems. There also exists regulatory ambiguity, resistance to adoption by the organizational set and economic impediments to the extensive utilization of AI in shipping.

Nevertheless, this is quite apparent where we are going in terms of maritime operations: it will be more and more influenced by smart technologies and data-driven autonomy. In hopes of making this transition successfully, stakeholders should collaborate to come up with international standards, invest in developing digital skills, and focus on integrating the human-AI collaboration frameworks. Instead of thinking of AIs as an alternative to human expertise, trying to fence them out, they should be seen as support to human decision-making, a reduction in the cognitive load, and a boost in near certainty of the complex operations under them.

To sum up, the future of shipping is exciting; it is more self-sufficient, safer and smarter, which is provided by remote intelligence at sea. With the growing development of technologies and the evolution of industry structures, the implementation of AI-enhanced vessel intelligence can transform the current system of ship operations, connection, and contribution to the sustainable global ocean framework.

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