

Review

Artificial Intelligence in Maritime Transportation: A Comprehensive Review of Safety and Risk Management Applications

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Abstract: Maritime transportation is crucial for global trade but faces significant risks and operational challenges. Ensuring safety is essential for protecting lives, the environment, and economic stability. This review explores the role of artificial intelligence (AI) in enhancing maritime safety and risk management. Key AI applications include risk analysis, crew resource management, hazardous material handling, predictive maintenance, and navigation systems. AI systems identify potential hazards, provide real-time decision support, monitor hazardous materials, predict equipment failures, and optimize shipping routes. Case studies, such as Wärtsilä's Fleet Operations Solution and ABB Ability™ Marine Pilot Vision, illustrate the benefits of AI in improving safety and efficiency. Despite these advancements, integrating AI poses challenges related to infrastructure compatibility, data quality, and regulatory issues. Addressing these is essential for successful AI implementation. This review highlights AI's potential to transform maritime safety, emphasizing the need for innovation, standardized practices, and robust regulatory frameworks to achieve safer and more efficient maritime operations.

Keywords: maritime safety; AI; risk management; crew resource management; hazardous material handling; predictive maintenance; navigation systems; maritime operations



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1. Introduction

Maritime transportation is essential for global trade, facilitating the movement of goods and raw materials across the world's oceans. Approximately 90% of global trade is carried by sea, underscoring its critical role in international commerce (United Nations Conference on Trade and Development [UNCTAD], 2020) [1,2]. However, this industry faces significant risks and operational challenges, including harsh weather, unpredictable sea states, and human error, which can lead to accidents such as collisions, groundings, and spills, posing substantial threats to human life, the environment, and economic stability [3–5].

Ensuring safety in maritime transportation is crucial. The International Maritime Organization (IMO) has established various regulations and standards aimed at enhancing maritime safety, reflecting the industry's commitment to minimizing risks and promoting a safety culture [6–9]. Effective safety measures are also essential for environmental protection, as shipping activities can lead to oil spills, chemical leaks, and other forms of pollution that severely impact marine ecosystems [7,10]. Additionally, maintaining safety is vital for economic stability, as accidents and disruptions can result in significant financial losses and impede global trade [11,12].

Given these challenges, there is a growing interest in leveraging advanced technologies, particularly artificial intelligence (AI), to enhance maritime safety and risk management. AI offers innovative solutions for risk assessment, predictive maintenance, seafarer resource management, and navigation, transforming the maritime industry by improving operational safety and efficiency [13,14].

This review aims to provide a comprehensive analysis of AI applications in maritime safety and risk management. It explores various AI technologies and their implementations in the maritime sector, highlighting their benefits, challenges, and future prospects.

Several recent reviews have explored AI applications in maritime contexts, focusing on specific areas such as autonomous vessels [15,16] and port operations [17]. This review differentiates itself by providing a broader analysis of AI's role in enhancing maritime safety across multiple domains, including risk management, crew resource management, and hazardous material handling. By synthesizing AI applications and case studies, this review aims to offer a comprehensive perspective not addressed in previous works.

The review focuses on issues such as navigation systems, which can greatly improve the work of the navigation officer by providing integrated data to assist in the navigator's decision-making and reduce time. The article also discusses the important aspect of managing the separation of transported dangerous goods, leading to a reduction in segregation time and the demonstration of conflicts between individual cargoes at the time of occurrence. The review addresses an aspect of the challenge of managing the wider risks on board a ship, from managing and complying with the necessary inspections and audits to supporting the navigator's decisions to avoid collisions. The article explains the relevance of AI in managing the ship's energy and reducing fuel consumption, thereby reducing harmful emissions. The article also discusses the possibilities of improving crew skills through the use of extensive AI resources.

Through a synthesis of recent research and case studies, this article underscores the significant contributions of AI to maritime safety and the overall resilience of the maritime industry.

Safety in maritime transportation refers to the measures and practices implemented to prevent accidents and incidents that could endanger human life, damage property, or harm the marine environment. This encompasses a wide range of activities, including regulatory compliance with international, national, and regional regulations and standards set by organizations such as the International Maritime Organization (IMO). These regulations cover various aspects of maritime operations, including ship construction, equipment, crew qualifications, and operational procedures [6–9].

Preventive measures include the implementation of systems and protocols designed to prevent accidents, such as regular maintenance, safety drills, and the use of advanced navigation and communication technologies. These measures aim to address potential risks before they lead to incidents [11,12]. Emergency preparedness and response involve the development of contingency plans and training programs to ensure that crew members are prepared to respond effectively to emergencies, such as oil spills, fires, and collisions. This includes the provision of necessary equipment and the establishment of coordination mechanisms with relevant authorities [7,10].

Risk management in maritime transportation involves the systematic identification, assessment, and mitigation of risks associated with maritime operations. Risk assessment is the process of identifying potential hazards, evaluating the likelihood of their occurrence, and assessing the potential impact on human life, property, and the environment. This often involves the use of risk assessment models and tools to analyze various risk scenarios [13,14]. Risk mitigation includes the implementation of strategies and measures to reduce the likelihood and impact of identified risks. This can involve engineering controls, administrative controls, and the use of advanced technologies such as AI for real-time monitoring and predictive analytics [13,14]. Continuous monitoring and review are essential for ongoing monitoring of maritime operations to detect new risks and evaluate the effectiveness of existing risk management measures. Regular reviews and updates to risk

management plans ensure that they remain relevant and effective in addressing emerging challenges [6–9] (Table 1).

Table 1. Overview of AI applications in maritime safety and risk management.

AI Application Area	Description	Key Benefits	Examples
Risk Analysis and Management	Identifying potential hazards and predicting risks using data analysis and machine learning.	Enhanced risk prediction and mitigation	Maersk’s AI-Powered Risk Management, DNV GL’s Veracity Platform
Crew Resource Management	Enhancing crew training and decision-making through AI-powered simulations and real-time support.	Improved training effectiveness and decision support	Wärtsilä’s SmartPredict System
Hazardous Material Handling	Monitoring and managing hazardous materials using AI systems for compliance and safety.	Increased safety and compliance	ABB Ability™ Marine Pilot Vision
Predictive Maintenance	Analyzing equipment data to predict and prevent failures, reducing downtime and costs.	Reduced downtime and maintenance costs	Kongsberg’s Kognifai Maritime Ecosystem
Navigation Systems	Optimizing routes, avoiding collisions, and monitoring environmental conditions with AI.	Enhanced navigation safety and efficiency	Wärtsilä’s Fleet Operations Solution, ABB Ability™ Marine Pilot Vision

Despite numerous advances, gaps remain in the integration of AI into maritime safety and risk management. Previous studies have focused primarily on individual applications of AI without a comprehensive analysis of their collective impact and integration challenges. This study addresses this gap by providing a detailed examination of how various AI technologies can be synergistically applied to enhance maritime safety and operational efficiency. By clarifying these concepts, this review provides a foundation for understanding how AI technologies can be applied to enhance safety and risk management in maritime transportation. The following sections will delve deeper into specific AI applications and their impact on the maritime industry.

2. Methodology

This section outlines the systematic approach employed to review and analyze the applications of artificial intelligence (AI) in maritime safety and risk management. The methodology is designed to ensure a comprehensive and objective assessment of existing research, case studies, and technological implementations within the maritime industry.

2.1. Literature Review

The literature review was conducted using a systematic approach across several academic databases, including Google Scholar, IEEE Xplore, Web of Science, and ScienceDirect. Keywords used in the search process included ‘AI in maritime safety’, ‘predictive maintenance in shipping’, ‘AI for risk management in maritime transport’, and ‘maritime AI navigation systems’. Studies were included based on the following criteria: (1) peer-reviewed articles, (2) published between 2010 and 2023, and (3) directly related to the application of AI in maritime safety, risk management, and operational efficiency. Additionally, relevant industry reports and white papers were included where they contributed significant insights into AI applications. Articles were initially screened by title and abstract, followed by full-text reviews to ensure relevance to the research questions (Figure 1).

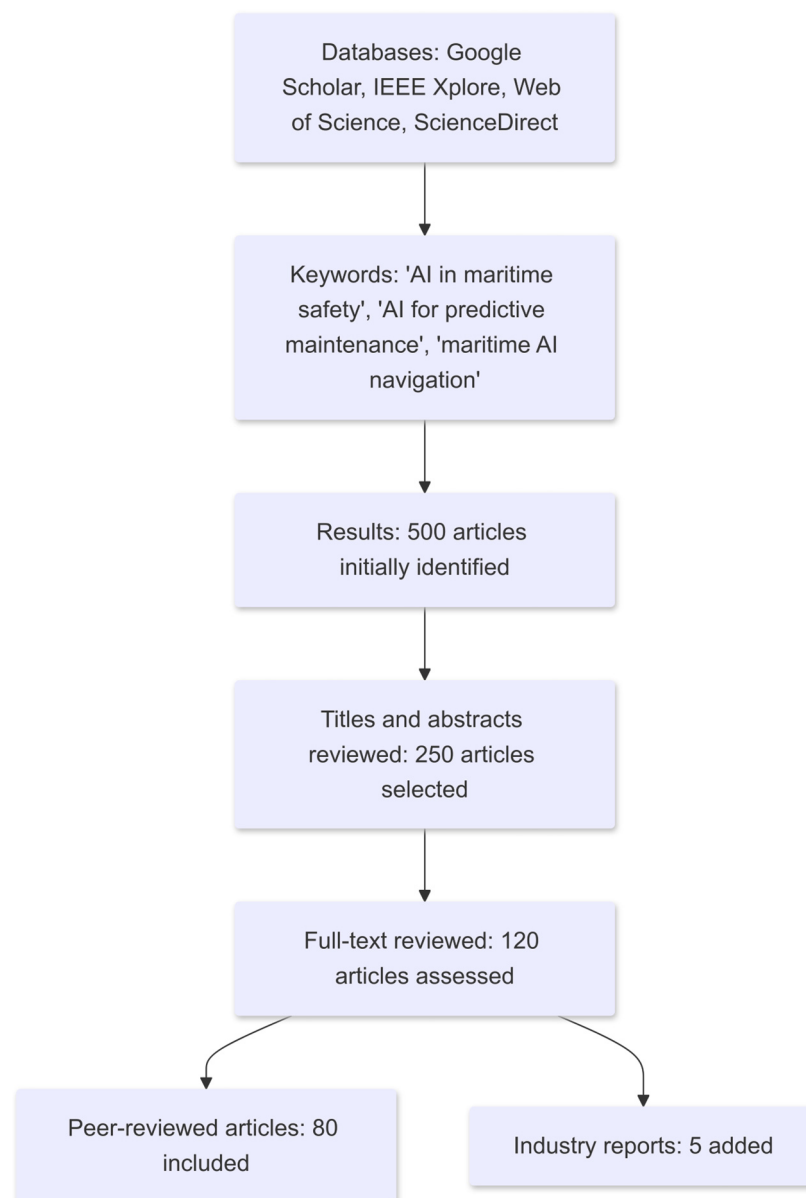


Figure 1. Literature search flow.

2.2. Data Collection

Data collection involved gathering information from the selected literature and extracting key insights related to AI applications in maritime safety and risk management. This included details on the types of AI technologies used, their specific applications, benefits, challenges, and case studies demonstrating successful implementations.

The data collection process was structured as follows:

1. Identification of relevant studies based on the inclusion criteria.
2. Extraction of key information from each study, including the AI technologies used, their applications, and outcomes.
3. Categorization of the extracted data into thematic areas such as risk assessment, predictive maintenance, crew management, navigation, and hazardous material handling.

2.3. Case Study Analysis

A case study analysis was conducted to provide concrete examples of AI applications in the maritime industry. Four key case studies were selected based on their relevance and the availability of detailed information:

1. Maersk's AI-powered risk management system.
2. DNV GL's Veracity platform for predictive maintenance and risk management.
3. Wärtsilä's SmartPredict system for enhanced navigation.
4. Shell's AI-enhanced navigational safety system.

For each case study, the following aspects were analyzed:

1. Description of the AI system and its components.
2. Implementation process and integration with existing systems.
3. Benefits and improvements observed.
4. Challenges encountered and solutions implemented.
5. Future prospects and scalability of the system.

To identify research gaps, a thorough analysis of the literature and case studies was performed. This involved comparing current AI applications and technologies with industry needs and challenges. Key areas where AI integration is lacking or could be improved were identified. The analysis aimed to highlight the practical and theoretical gaps that the current study seeks to address.

The final step involved synthesizing the collected data and analysis results into a coherent narrative. The findings were structured to provide a comprehensive overview of AI applications in maritime safety and risk management. The report includes:

1. An introduction to the importance of maritime safety and the role of AI.
2. Detailed descriptions of AI technologies and their specific applications.
3. Analysis of case studies demonstrating successful implementations.
4. Identification of benefits, challenges, and future prospects.
5. Recommendations for effective AI integration in maritime operations.

This structured approach ensures that the review provides a thorough and objective assessment of AI applications in maritime safety and risk management, offering valuable insights for researchers, industry stakeholders, and policymakers.

3. AI Implementations in Maritime Transport Systems

AI, with its processing capabilities and ability to integrate multiple systems, has the potential to enhance and improve many tasks on the vessels. The maritime industry is increasingly interested in applying advanced AI and ML technologies to address issues related to sustainability, efficiency, and regulatory compliance [15]. This section describes the significance of using AI algorithms in maritime systems (Figure 2):

1. Navigation Systems—AI algorithms assist in navigational decision-making to avoid collisions and enhance the accuracy of a ship's navigational position, thereby increasing navigational safety;
2. Hazardous Material Handling—AI-based tools that provide information on the rules for segregation and separation of hazardous cargo eliminate the possibility of human error, thereby preventing the risk of explosions, fires, and marine pollution;
3. Risk Analysis and Management—AI algorithms enable risk management on ships during navigational tasks, mooring operations, technical inspections, regular operations, and shipyard repairs;
4. Crew Resource Management—Tools that support the smooth operation of sea and port watches, as well as maintenance work on the ship, while ensuring compliance with rest time requirements for the crew in relation to working hours;
5. Energy Efficiency—AI that supports route planning between ports and controls the use of the main engine and RPM (revolutions per minute) significantly reduces fuel costs and protects the marine environment by lowering exhaust emissions. Sustainable energy consumption should not be limited to the ship while it is at sea; it must also be considered during its time in port. The application of machine learning (ML), as a key subdomain of artificial intelligence (AI), can be viewed as a component of the digital transformation process aimed at advancing green practices in maritime port logistics. In the realm of environmental sustainability, emissions and energy consumption are

the most commonly studied issues. Future research is distinguished by two broad directions: shifting focus to a greater diversity of machine learning approaches for promoting sustainability in ports and leveraging new perspectives to implement more environmentally friendly practices in port operations [1];

6. Predictive Maintenance—Managing, controlling, and executing repair and maintenance work requires proper time management and planning according to the operating conditions of the ship. AI algorithms that analyze historical inspection and maintenance data improve the planning and management of upcoming inspections, eliminating the possibility of missing necessary repairs and periodic maintenance.

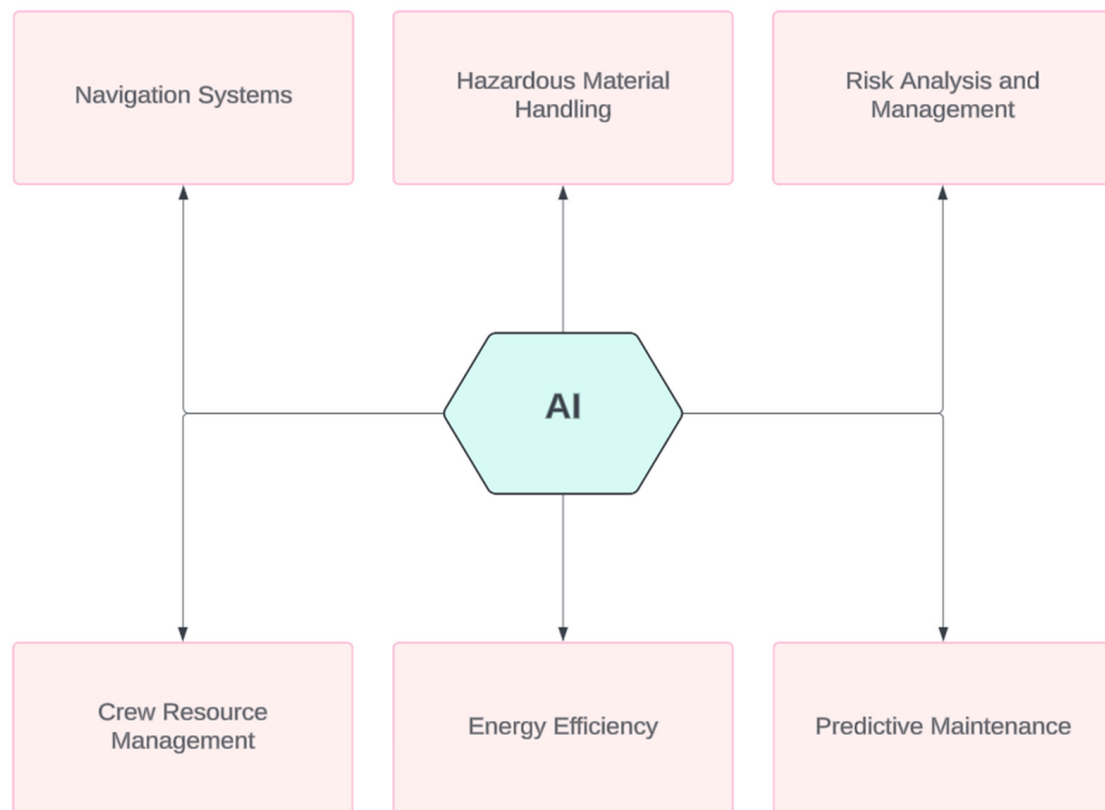


Figure 2. Potential AI implementations in maritime transport systems.

The use of artificial intelligence is not only aimed at managing maintenance on ships but also at creating tools to support shore-based inspectors carrying out Port State Control (PSC) inspections. This inspection is seen as a safeguard to protect maritime safety, protect the marine environment, and ensure decent working and living conditions for seafarers. A substandard vessel may be detained during an inspection if serious deficiencies are found on board. However, developing accurate models to predict ship detention based on general ship factors (e.g., age of ship, type, flag), dynamic factors (e.g., flag changes in the ship), and historical inspection factors (e.g., the total number of previous detentions in PSC inspections, time since last PSC inspection, number of deficiencies in last PSC inspection) prior to an inspection is not a trivial task, as low detention rates lead to a highly unbalanced dataset of inspection records. To address this problem, experts propose a classification model called balanced random forest (BRF) for predicting vessel detentions. Numerical experiments show that this model can achieve an average improvement of 73.72% in identifying detained vessels, using the Hong Kong port as an example [16].

3.1. AI in Risk Analysis and Management

Artificial intelligence (AI) has revolutionized the field of risk identification in maritime transportation by leveraging advanced data analysis and machine learning (ML) techniques. Traditionally, risk identification in maritime operations relied on historical data, expert judgment, and manual inspections. However, these methods often fall short of capturing the dynamic and complex nature of maritime risks [11,17].

AI systems can process vast amounts of data from various sources, including vessel tracking systems, weather forecasts, maintenance records, and incident reports. By analyzing these data, AI algorithms can identify patterns and correlations that may indicate potential hazards. For instance, machine learning models can detect anomalies in vessel movements, which might suggest mechanical issues or navigational errors. Additionally, AI can assess environmental conditions, such as sea state and weather patterns, to predict hazardous situations like rough seas or storms [18,19].

Furthermore, AI enhances situational awareness by integrating real-time data from multiple sensors and information systems. This comprehensive data analysis allows for the early detection of risks, enabling timely interventions to prevent accidents. For example, AI-powered systems can monitor engine performance and alert operators to potential failures before they lead to critical incidents [13,20].

Predictive analytics, a key application of AI in maritime risk management, involves using historical data and machine learning models to forecast future risks and their potential impact. By predicting the likelihood of various risk scenarios, maritime operators can proactively implement preventive measures and mitigate potential hazards.

One of the primary benefits of predictive analytics in maritime transportation is its ability to enhance decision-making. AI models can evaluate numerous risk factors simultaneously, providing a more comprehensive risk assessment than traditional methods. For example, predictive models can analyze factors such as vessel age, maintenance history, route characteristics, and crew experience to estimate the probability of mechanical failures or accidents [14,21].

Moreover, predictive analytics can optimize maintenance schedules by predicting equipment failures before they occur. This approach, known as predictive maintenance, helps reduce unplanned downtime, lowers maintenance costs, and improves overall vessel reliability. AI algorithms can analyze sensor data from critical machinery to detect early signs of wear and tear, enabling timely repairs and replacements.

AI systems process vast amounts of data from various sources, including vessel tracking systems, weather forecasts, maintenance records, incident reports, and real-time sensor data from onboard systems monitoring engine performance, hull stress, and other critical parameters.

Several AI algorithms and methods are employed to analyze these data. Neural networks, for instance, are used for pattern recognition and anomaly detection. They can identify unusual vessel movements, indicating potential mechanical issues or navigational errors. Decision trees are utilized for classification and decision-making, helping to predict the likelihood of specific incidents based on historical data, such as assessing the risk of collision based on vessel speed, direction, and proximity to other ships.

Support vector machines (SVMs) are employed for classification and regression analysis, predicting outcomes like potential equipment failures by analyzing patterns in sensor data. Bayesian networks, as probabilistic models, estimate the likelihood of various risk scenarios by combining different data sources. For example, they can predict the probability of adverse weather conditions affecting navigation safety. Cluster analysis, used for grouping similar data points, helps identify patterns and trends in large datasets, such as clustering vessel routes to highlight common risk areas requiring enhanced monitoring.

AI-driven predictive analytics also play a crucial role in voyage planning. By forecasting potential risks along specific routes, AI systems can recommend safer and more efficient navigation strategies. This capability is particularly valuable in avoiding haz-

ardous weather conditions and congested shipping lanes, thereby enhancing the safety and efficiency of maritime operations [14,22].

However, predictive models also have their limitations, which can significantly affect the results generated by the model.

The main limitation of predictive systems stems from the very nature of forecasting—there is no certainty that the predicted events will actually happen. Therefore, it is important to remember that predictive outcomes can only be probabilities, not certain facts. Additionally, many predictive models are based on certain assumptions, such as linearity or independence of variables. If these assumptions are incorrect, the model may generate inaccurate predictions. It is also important to be aware of the possibility of overfitting the model to the training data or of training a model that is too general (underfitting). Overfitting the model to the data makes it less effective in forecasting with new data. On the other hand, a model that is too general may fail to capture important patterns.

The importance of data quality and availability cannot be overlooked, as predictive models are only as good as the data on which they are based. Poor data quality, missing information, or data bias can lead to incorrect results. It is therefore crucial that data is properly collected, stored, and managed so that a reliable and accurate predictive model can be created.

These limitations of the predicting models may be relevant when using models to predict the weather in a given area and to determine a safe route for a ship from port to port. A model trained on historical data may fail to take into account the variables of current weather conditions or perform poorly in seasonality. This can result in the ship being directed into unsafe navigation areas or, conversely, in the model incorrectly predicting bad weather and forcing the ship to take a longer and less economical route. This in turn leads to an increase in fuel consumption, causing costs and higher emissions of environmentally harmful pollutants.

These constraints also affect the predictive models used to optimize engine performance and predict failures. An AI-based predictive model that is supposed to adjust engine parameters in real time to ensure optimal engine performance and lead to fuel savings and emission reductions may in fact steer the engine inefficiently and degrade expected performance.

Another important aspect is the models used to support the ship's decision to avoid collision with another vessel or land obstacles. Such models must be monitored by humans in real time, as the variability of the maritime environment and the dynamic movement of the ship are incredibly difficult to predict. Over-reliance on model predictions could lead to disasters in the maritime environment.

When using predictive models in the maritime environment, especially for systems that are used in real time on board ships to support human decision-making, it is crucial to ensure proper crew training and awareness of the potential limitations of such models.

Case Studies

Several case studies demonstrate the successful implementation of AI in maritime risk management, highlighting its potential to enhance safety and operational efficiency. To address the reviewer's feedback, we will analyze each case study following a systematic methodology, identifying specific barriers and opportunities (Table 2).

Table 2. Case studies of AI implementations in maritime operations.

Case Study	AI Application	Implementation Details	Outcome/Impact
Wärtsilä's Fleet Operations Solution	Navigation Systems	Integration of route optimization, collision avoidance, and environmental monitoring in a single platform.	Safer and more efficient voyages through dynamic route adjustments
ABB Ability™ Marine Pilot Vision	Situational Awareness and Collision Avoidance	AI-driven system using sensors to create a 3D model of surroundings and provide real-time guidance.	Enhanced navigation safety during complex maneuvers
Kongsberg's Kognifai Maritime Ecosystem	Navigation and Environmental Monitoring	Continuous monitoring of environmental conditions and vessel performance for optimized navigation.	Reduced transit time and fuel consumption in congested areas
Maersk's AI-Powered Risk Management	Risk Analysis and Management	AI algorithms for risk identification and mitigation in maritime operations.	Improved risk prediction and proactive risk management
DNV GL's Veracity Platform	Risk Analysis and Compliance	Platform for integrating data from various sources to enhance risk management and regulatory compliance.	Enhanced safety and regulatory compliance through data integration

Case Study 1: Maersk's AI-Powered Risk Management

Maersk, a global leader in container shipping, has integrated AI into its risk management processes. The company uses AI to analyze data from its fleet, including vessel performance, route characteristics, and environmental conditions. By identifying patterns and anomalies, the AI system helps Maersk predict and mitigate risks associated with navigation, mechanical failures, and environmental hazards. This implementation has enhanced Maersk's ability to ensure the safety of its vessels and crew while maintaining efficient operations [23].

The AI system leverages machine learning algorithms to process real-time data from various sensors and historical data. This comprehensive analysis allows Maersk to foresee potential issues and take preventive measures, thereby reducing the likelihood of accidents and improving operational efficiency [24].

Barriers:

- Integration with existing systems and data sources.
- Ensuring data quality and reliability from diverse sources.
- Overcoming resistance to change among crew members and stakeholders.

Opportunities:

- Enhanced predictive capabilities with continuous data integration.
- Improved operational efficiency through proactive maintenance.
- Reduction in accidents and associated costs.

Case Study 2: DNV GL's Veracity Platform

DNV GL, a leading maritime classification society, developed the Veracity platform, which utilizes AI for predictive maintenance and risk management. The platform collects and analyzes data from ship systems, including engines, pumps, and navigation equipment. By applying machine learning models to these data, the platform can predict equipment failures and recommend maintenance actions. This proactive approach helps ship operators maintain vessel safety and reliability while minimizing operational disruptions [25].

The Veracity platform enables continuous monitoring of critical systems, providing insights into their condition and performance. This real-time monitoring capability helps operators detect early signs of wear and tear, allowing for timely maintenance and reducing

the risk of unexpected failures. The platform has been successfully implemented on numerous vessels, demonstrating its effectiveness in enhancing safety and operational efficiency [26,27].

Barriers:

- Integration with legacy systems and varied equipment.
- Data security and privacy concerns.
- High initial investment costs for deployment.

Opportunities:

- Enhanced real-time monitoring, leading to reduced downtime.
- Increased lifespan of equipment through timely maintenance.
- Potential for scalable solutions across the fleet.

Case Study 3: Wärtsilä's SmartPredict System

Wärtsilä, a global leader in smart technologies for marine and energy markets, has developed the SmartPredict system, which uses AI to enhance maritime safety and operational efficiency. SmartPredict is an advanced decision-support tool that assists in ship maneuvering by providing predictive insights based on real-time data [14].

The system utilizes machine learning algorithms to analyze data from the vessel's sensors, including speed, heading, and environmental conditions. By predicting the vessel's future positions and potential trajectories, SmartPredict helps operators make informed decisions to avoid collisions and grounding. The system also provides visualizations and alerts, enabling proactive interventions to mitigate risks [27,28].

SmartPredict has been deployed on various vessels, demonstrating its ability to improve safety during critical maneuvers, such as docking, undocking, and navigating through congested waters. The system's predictive capabilities enhance situational awareness and reduce the risk of accidents, contributing to safer and more efficient maritime operations.

Barriers:

- Ensuring data accuracy and real-time processing.
- Training crew to effectively use and trust the system.
- Integration with existing navigational tools and systems.

Opportunities:

- Improved safety and efficiency during critical maneuvers.
- Reduction in collision and grounding incidents.
- Enhanced situational awareness and decision-making support.

Case Study 4: Shell's AI-Enhanced Navigational Safety

Shell, a leading global energy company, has implemented AI technologies to enhance navigational safety for its fleet. The AI system integrates data from multiple sources, including weather forecasts, sea state information, and vessel performance metrics, to provide real-time decision support to ship operators. By analyzing these data, the AI system can predict potential navigational hazards and recommend optimal routes to avoid adverse conditions [29].

This AI-enhanced navigational system has been particularly effective in ensuring the safety of Shell's tankers, which often operate in challenging and remote environments. The system's predictive capabilities help operators avoid areas with high risk of collisions, grounding, or extreme weather, thereby reducing the likelihood of accidents and enhancing overall fleet safety [30,31].

Barriers:

- Ensuring reliable data transmission in remote areas.
- Integration with existing navigational and operational systems.

- Overcoming initial implementation costs and complexity.

Opportunities:

- Enhanced route optimization, leading to fuel savings and reduced emissions.
- Increased safety and reduced risk of accidents in challenging environments.
- Improved decision support through real-time hazard prediction.

3.2. AI in Crew Resource Management

Artificial intelligence (AI) is increasingly being integrated into maritime operations to provide real-time decision support to seafarers, enhancing their performance and safety. However, to substantiate these claims, it is crucial to include specific examples and empirical data demonstrating the practical benefits of AI in seafarer resource management. AI-powered training simulations have become essential tools in enhancing seafarer resource management (SRM) within the maritime industry. These simulations use advanced AI algorithms to create realistic and dynamic training scenarios that mimic real-world maritime operations. By exposing seafarers to various operational challenges and emergency situations in a controlled environment, AI-driven simulations significantly improve their decision-making, problem-solving, and teamwork skills [32,33].

One of the key advantages of AI-powered simulations is their ability to adapt to the trainee's performance. Machine learning algorithms can analyze the actions of trainees in real time and adjust the difficulty level and complexity of scenarios accordingly. This personalized approach ensures that each crew member receives training that is tailored to their specific needs and skill levels [34,35].

Furthermore, AI simulations provide instant feedback and detailed performance analysis. Trainees can review their actions and decisions, learn from their mistakes, and understand the consequences of their actions without the risks associated with real-life training. This iterative learning process helps to build confidence and competence, preparing crew members to handle various maritime situations effectively [36,37].

AI systems are increasingly being integrated into maritime operations to provide real-time decision support to crew members. These systems utilize data from various sources, including sensors, weather forecasts, and navigation systems, to offer actionable insights and recommendations during operations [37].

AI systems also provide real-time decision support to seafarers during operations. These systems utilize data from various sources, including sensors, weather forecasts, and navigation systems, to offer actionable insights and recommendations. For example, an AI system can monitor a ship's position, speed, and heading along with external factors such as traffic density and weather conditions to predict potential collisions or grounding incidents. The system can then alert the seafarers and recommend evasive maneuvers to avoid accidents [13,21].

In addition to risk management, AI decision support systems can enhance operational efficiency. By optimizing route planning based on real-time data, these systems can help ships reduce fuel consumption, avoid delays, and improve overall voyage performance. The ability to process and analyze data continuously ensures that the crew has access to the most up-to-date information, enabling them to make informed decisions quickly [38,39].

The integration of AI in crew resource management has a profound impact on maritime safety. By enhancing training and providing real-time decision support, AI technologies contribute to a significant reduction in human errors, which are a leading cause of maritime accidents [40].

AI-powered training simulations prepare crew members to handle a wide range of scenarios, from routine operations to emergency situations. This comprehensive training improves their ability to respond effectively to unforeseen events, reducing the likelihood of accidents caused by inadequate training or poor decision-making. Studies have shown that crews trained with AI simulations demonstrate higher levels of competence and confidence in real-world operations [34].

Real-time decision support systems enhance situational awareness by providing crew members with critical information and predictive insights. This increased awareness allows for proactive risk management, enabling the crew to address potential issues before they escalate into serious incidents. For instance, AI systems that monitor environmental conditions and vessel performance can alert the crew to dangerous situations, such as approaching storms or mechanical failures, allowing for timely preventive measures.

Human error remains a significant factor in maritime accidents. AI technologies help mitigate this risk by supporting decision-making processes and automating routine tasks. For example, AI-driven navigation systems can reduce the cognitive load on the crew by handling complex calculations and providing clear recommendations, thereby minimizing the chances of errors caused by fatigue or information overload. Furthermore, AI can continuously monitor crew performance and provide reminders or warnings when deviations from standard procedures are detected.

For instance, Kongsberg Maritime's K-Sim platform offers highly realistic training scenarios ranging from standard operational procedures to emergency responses. K-Sim's AI capabilities allow it to adapt to the trainee's performance, providing tailored feedback and enhancing the learning experience. Research has shown that seafarers trained with K-Sim exhibit improved operational performance and decision-making skills, contributing to safer maritime operations [17,40,41].

The Nautilus 3D is an AI-based simulation platform designed to enhance maritime training by providing immersive, interactive scenarios. It uses AI to create realistic training environments that adapt to the actions of the trainees. The platform has been used to train crews on various aspects of maritime operations, including navigation, emergency response, and maintenance procedures. Evaluations of the Nautilus 3D system have demonstrated its effectiveness in improving crew preparedness and reducing the incidence of errors during actual operations [38,42,43].

In conclusion, the application of AI in crew resource management represents a significant advancement in maritime safety. Through enhanced training simulations and real-time decision support, AI technologies equip crew members with the skills and information needed to operate safely and efficiently. The ongoing development and adoption of these technologies promise to further reduce the risk of accidents and improve the overall safety of maritime transportation.

3.3. AI in Hazardous Material Handling

AI-powered training simulations have become essential tools in enhancing seafarer resource management (SRM) within the maritime industry. These simulations use advanced AI algorithms to create realistic and dynamic training scenarios that mimic real-world maritime operations. By exposing seafarers to a variety of operational challenges and emergency situations in a controlled environment, AI-driven simulations significantly improve their decision-making, problem-solving, and teamwork skills.

AI systems have significantly advanced the real-time monitoring of hazardous materials in maritime transportation. These systems utilize a combination of sensors, data analytics, and machine learning algorithms to continuously monitor the status and condition of hazardous materials on board ships. This real-time monitoring capability ensures that any potential risks are identified and addressed promptly, thereby enhancing safety and compliance with regulatory standards [43–45].

Key features of AI-powered real-time monitoring include sensor integration, where AI systems integrate data from various sensors that monitor parameters such as temperature, pressure, humidity, and chemical composition. These sensors provide continuous data streams that AI algorithms analyze to detect anomalies and potential risks. Advanced data analytics techniques process the sensor data to identify patterns and trends that may indicate hazardous conditions. For example, an unexpected increase in temperature or pressure within a containment unit can signal a potential leak or failure. AI algorithms can also predict when maintenance is required based on the condition of the hazardous

materials and the containment systems, helping to prevent incidents by ensuring that equipment is serviced before a failure occurs. Additionally, AI systems ensure that the handling and storage of hazardous materials comply with safety regulations and standards. By continuously monitoring conditions, these systems help maintain adherence to protocols and provide documentation for regulatory compliance [46–48].

Automated response systems driven by AI are crucial for managing hazardous material incidents effectively. These systems can quickly and accurately assess a situation, determine the appropriate response, and execute actions to mitigate risks. The use of AI in automated response systems enhances the speed and efficiency of emergency responses, reducing the potential impact of hazardous material incidents [49–51]. AI systems detect incidents through real-time monitoring and data analysis. When a hazardous condition is identified, the system triggers an alert and begins the response process. AI algorithms evaluate the severity of the incident and determine the best course of action, considering various factors such as the type of hazardous material, the extent of the breach, and environmental conditions. The system can automatically execute response actions, such as activating containment measures, shutting down affected systems, and notifying emergency response teams. These automated actions help to quickly control the situation and prevent the spread of hazardous materials. Additionally, AI systems facilitate communication and coordination among seafarers and emergency responders. By providing real-time information and guidance, these systems ensure that all parties are informed and can collaborate effectively during an incident [49–51].

While AI systems offer significant benefits in hazardous material handling, several challenges and limitations must be addressed to ensure their effective implementation. The reliability of data is crucial for the effective functioning of AI systems. Maritime environments are dynamic and unpredictable, leading to inconsistencies in data collection. Sensors may not function optimally under all conditions due to exposure to saltwater, extreme temperatures, and mechanical vibrations, which can result in gaps or inaccuracies in the collected data [49–52].

Integrating AI systems with existing maritime infrastructure can be challenging. Maritime operations often rely on legacy systems that were not designed to integrate with modern AI technologies, leading to compatibility issues. Extensive modifications and upgrades to current infrastructure are often necessary, which can be costly and time-consuming [51,52]. Successful AI integration also requires consideration of cultural and environmental factors within the maritime industry. Seafarers and other stakeholders must adapt to new technologies, which necessitates training and the fostering of a supportive atmosphere. Resistance to change and lack of familiarity with AI systems can hinder their effective implementation [49–52].

The effectiveness of automated response systems depends on the quality and timeliness of the data received. In remote maritime environments with limited connectivity, real-time data transmission can be challenging, potentially delaying critical response actions [52].

To address these challenges and enhance the effectiveness of AI in hazardous material handling, several recommendations are proposed. Enhancing sensor technology to improve durability and reliability under maritime conditions is crucial. Standardizing data collection methods and establishing robust data management practices can help maintain data quality and reliability. Investing in advanced data transmission technologies, such as satellite communication systems, can mitigate connectivity issues and enhance real-time data availability. A phased approach to AI integration, starting with pilot projects and gradually scaling up, allows organizations to identify and address potential issues early on, ensuring smoother adoption. Comprehensive training programs for seafarers and other stakeholders are vital to equip them with the necessary skills to operate AI tools and interpret their outputs, fostering a supportive atmosphere for technological integration.

In further consideration of this section, it is also necessary to discuss the possible risks arising from the use of AI systems to control dangerous cargo and the potential consequences of the failure of these systems (Figure 3).

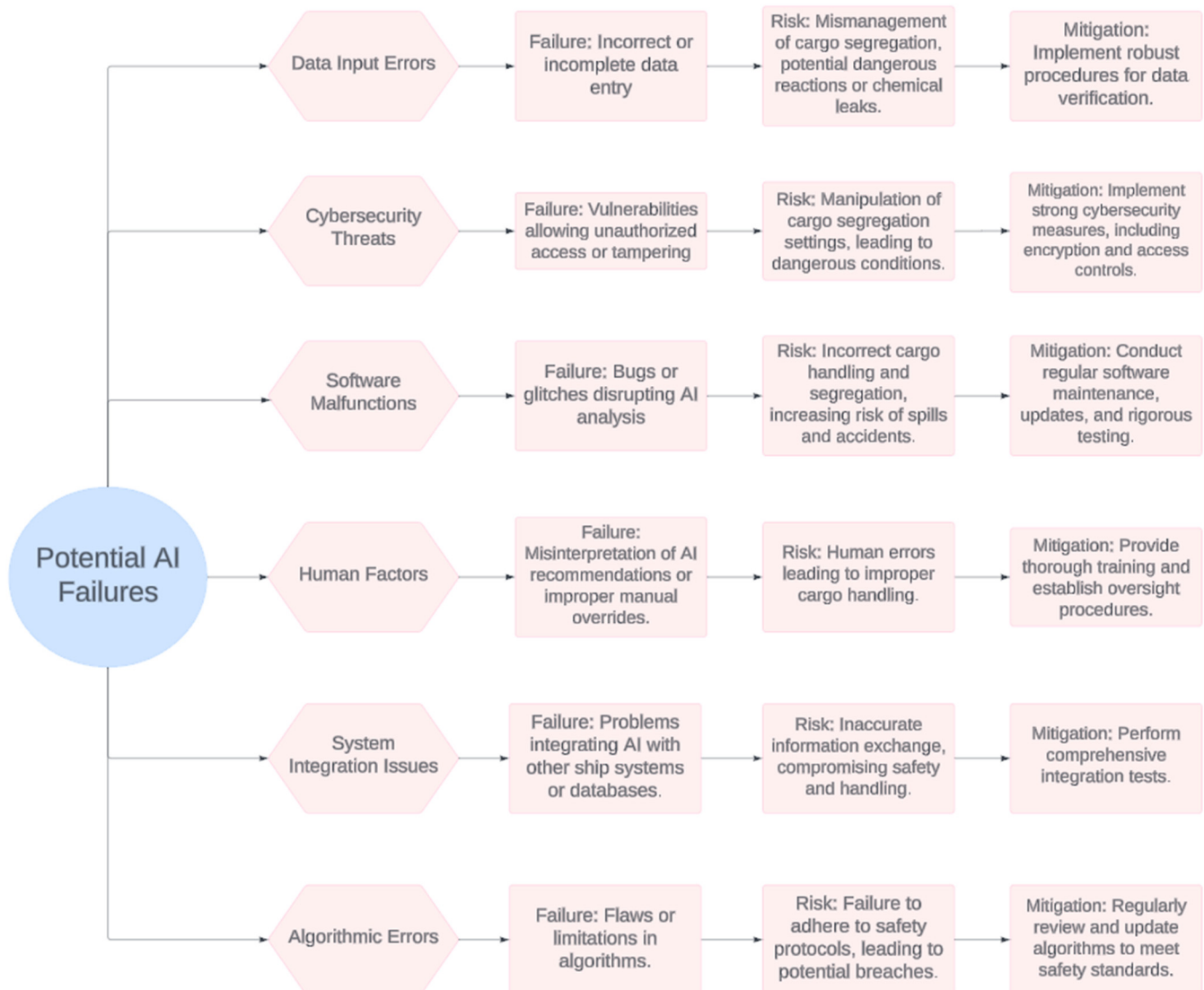


Figure 3. Potential risks of AI system failures in the handling of hazardous cargo and preventive measures.

1. Data Input Errors

The data input errors can be defined as the most basal risk that pertains to any inaccuracies while entering data and other data input problems such as non-completed forms or missing pages. These errors can, for instance, cause improper cargo separation and increase the likelihood of adverse reactions from the chemicals or leaks occurring during the movements. It is necessary in such a case to have very strict processes in place for the validation of the data before the AI system begins processing it. The likelihood of these errors occurring can be greatly reduced through the use of standardized and complete procedures to guide the applications of data input processes.

2. Software Malfunctions

AI software responsible for managing hazardous cargo can also be vulnerable to bugs or glitches, which may disrupt its analysis. Due to such malfunctions, spills and

other accidents aboard the vessel, such as cargo being handled incorrectly, may escalate. Appropriate measures to reduce these risks to a minimum include routine maintenance, systematic upgrades of the relevant software, and thorough cleansing of the software to allow only the safe ones to remain bundled. It provides assurance of the integrity of the system due to the readiness and operation of the software.

3. Algorithmic Errors

Other egregious concerns are those associated with the existence of deficiencies or shortcomings in AI algorithms. Such errors may also lead to a situation where the system deviates from the safety measures and regulations, increasing the risk of breaches. This can be solved through routine checks and revisions of the algorithms to make certain that security is up-to-date. Such failures in AI systems can also be avoided by effective and constant modification of the system algorithms.

4. System Integration Issues

Even in cases where AI systems are integrated into the ship systems, AI integration problems can also occur. Poor integration of the two systems may result in poor information exchange, and the safety of the cargo operations may not be guaranteed. It is important to test the entire integration so that there is a guarantee that all the systems will exchange information well and there are no problems with the information provided.

5. Cybersecurity Threats

Given that AI systems are increasingly connected, they are also susceptible to cybersecurity threats. Vulnerabilities in the system could allow unauthorized access or tampering, leading to the manipulation of cargo segregation settings. This could create dangerous conditions on board. To mitigate this risk, implementing strong cybersecurity measures, such as encryption and access controls, is crucial. A robust cybersecurity framework will protect the system from external threats.

6. Human Factors

Misinterpretation of AI recommendations or improper manual overrides can lead to human errors in cargo handling. These errors might occur due to inadequate training or misunderstandings of the AI system's outputs. To prevent such occurrences, it is necessary to provide thorough training for all personnel and establish clear oversight procedures to ensure proper decision-making.

By addressing both the benefits and challenges of AI in hazardous material handling, this study provides a more nuanced and realistic view. This balanced perspective enhances the credibility and depth of the research, offering valuable insights into the practical applications and limitations of AI in maritime operations (Table 3).

Case Studies

Several case studies demonstrate the successful implementation of AI in maritime risk management, particularly in hazardous material handling, highlighting its potential to enhance safety and operational efficiency. To address the reviewer's feedback, we will analyze each case study following a systematic methodology, identifying specific barriers and opportunities.

Case Study 1: Hapag-Lloyd's Real-Time Hazardous Material Monitoring

Hapag-Lloyd, a leading global shipping company, has implemented an AI-powered system for the real-time monitoring of hazardous materials on its vessels. The system uses a network of sensors to continuously track the conditions of hazardous cargo, such as temperature and pressure. AI algorithms analyze the sensor data to detect anomalies and potential risks [53].

Table 3. AI in hazardous material handling.

Aspect	Description	Benefits	Examples
Real-Time Monitoring	AI systems continuously monitor hazardous materials, ensuring compliance with safety protocols and detecting anomalies.	Enhanced safety, early detection of potential hazards	Real-time monitoring systems in chemical tankers [53–55]
Automated Response Systems	AI-driven automated systems that can initiate immediate response actions in case of hazardous material incidents.	Quick and efficient response, minimized human exposure	Automated fire suppression systems [56,57]
Data Analytics and Prediction	AI analyzes historical data to predict potential hazardous material incidents and optimize handling processes.	Proactive risk management, reduced incidents	Predictive analytics in cargo handling [54–56]
Regulatory Compliance	AI systems help ensure adherence to international and local regulations regarding hazardous materials.	Improved compliance, avoidance of fines and legal issues	Compliance management systems [55–57]
Incident Management	AI supports the management of hazardous material incidents by providing real-time data and response recommendations.	Efficient incident resolution, reduced impact on operations	Incident management platforms [54,56,57]

In one instance, the system identified a significant temperature increase in a container carrying flammable materials. The AI system triggered an alert, and the crew was able to take immediate action to prevent a potential fire. This real-time monitoring capability has enhanced Hapag-Lloyd's ability to manage hazardous materials safely and comply with international regulations [54].

Barriers:

- Ensuring sensor accuracy and reliability under harsh maritime conditions.
- Integration with existing monitoring systems.
- Training crew to respond effectively to AI-generated alerts.

Opportunities:

- Enhanced safety through real-time monitoring and early risk detection.
- Improved compliance with international safety regulations.
- Reduction in incidents involving hazardous materials.

Case Study 2: Evergreen Marine's AI-Powered Compliance Monitoring

Evergreen Marine, a major shipping company, has implemented an AI-powered compliance monitoring system for hazardous materials. The system uses sensors and data analytics to ensure that the handling and storage of hazardous materials comply with safety regulations. AI algorithms continuously analyze data to identify any deviations from compliance protocols [54,55].

The system has been instrumental in maintaining Evergreen Marine's adherence to international safety standards. During a routine operation, the AI system detected that a container carrying hazardous chemicals was not stored at the required temperature. The system alerted the crew, who were able to take corrective action to ensure compliance and prevent potential risks [56,58].

Barriers:

- Maintaining continuous and reliable data transmission.
- Integration with legacy compliance systems.
- Ensuring data security and privacy.

Opportunities:

- Enhanced regulatory compliance through continuous monitoring.

- Prevention of incidents through early detection of non-compliance.
- Increased operational efficiency by reducing manual compliance checks.

These case studies highlight the transformative impact of AI in hazardous material handling in maritime transportation. By providing real-time monitoring, predictive maintenance, and automated response capabilities, AI systems enhance safety, ensure regulatory compliance, and reduce the risk of hazardous material incidents. Addressing the identified barriers and leveraging the opportunities can further enhance the effectiveness and adoption of AI technologies in the maritime industry.

3.4. AI in Predictive Maintenance

Predictive maintenance powered by AI is revolutionizing the maritime industry by enabling a shift from reactive to proactive maintenance strategies. AI systems analyze vast amounts of equipment data to predict potential failures and schedule maintenance activities before issues occur. This approach relies on advanced machine learning algorithms and data analytics to provide insights into equipment health and performance [44,45].

3.4.1. Data Collection

AI systems collect data from a wide array of sensors embedded in maritime equipment. These sensors monitor parameters such as vibration, temperature, pressure, and wear rates. The reliability and accuracy of these data are crucial for the effectiveness of predictive maintenance. However, maritime environments are dynamic and harsh, often leading to inconsistencies in data collection due to sensor malfunctions caused by exposure to saltwater, extreme temperatures, and mechanical vibrations. Ensuring high-quality and reliable data collection is a significant challenge that needs to be addressed [46,47].

3.4.2. Algorithm Development

Machine learning algorithms process the sensor data to identify patterns and anomalies that indicate potential failures. These algorithms can learn from historical data and continuously improve their accuracy in predicting equipment issues. AI creates predictive models that forecast the remaining useful life of equipment components. These models help maintenance teams schedule interventions at optimal times, reducing the risk of unexpected breakdowns. Continuous monitoring of equipment conditions allows AI systems to provide real-time alerts when performance deviates from normal parameters, indicating the need for maintenance [48,49].

3.4.3. Implementation Challenges

Implementing AI-driven predictive maintenance in the maritime industry involves several challenges. Integrating AI systems with existing maritime infrastructure can be complex due to compatibility issues with legacy systems. Extensive modifications and upgrades are often necessary, which can be costly and time-consuming [49,50]. Additionally, the effectiveness of predictive maintenance relies on real-time data transmission, which can be challenging in remote maritime environments with limited connectivity [52]. Overcoming these implementation challenges requires significant investment in technology and infrastructure.

3.4.4. Benefits and Opportunities

Implementing AI-driven predictive maintenance offers several significant benefits for maritime operations. By predicting equipment failures before they occur, AI enables timely maintenance interventions, preventing unplanned downtime. This ensures that ships remain operational and on schedule, reducing delays in maritime transportation [53–55]. Predictive maintenance helps in planning maintenance activities more efficiently. By scheduling maintenance based on actual equipment conditions rather than fixed intervals, companies can avoid unnecessary maintenance tasks and extend the life of equipment components, resulting in significant cost savings [53–55]. Regular monitoring and timely

maintenance of critical equipment reduce the likelihood of malfunctions that could lead to accidents or hazardous situations. This proactive approach enhances the overall safety of maritime operations and protects the crew and cargo [53–55].

While AI offers significant advantages in predictive maintenance, it is essential to critically examine the potential risks and limitations. Over-reliance on AI systems can lead to complacency, where seafarers and maintenance personnel may neglect traditional maintenance practices and their own vigilance. Additionally, AI systems are only as good as the data they are trained on; poor-quality or biased data can lead to inaccurate predictions and potential failures. There are also concerns about the workforce implications, as increased automation could reduce the demand for certain roles, necessitating retraining and upskilling of affected workers [55–60].

A balanced discussion of AI in predictive maintenance must consider these risks alongside the benefits. While AI has the potential to significantly enhance maritime safety and efficiency, it should be viewed as a complementary tool that supports, rather than replaces, human expertise and decision-making. Ensuring that seafarers remain actively involved in maintenance processes is crucial to maintaining a high standard of safety and operational reliability.

By enabling data-driven maintenance strategies, AI helps companies reduce downtime, lower maintenance costs, and enhance operational safety, contributing to more efficient and reliable maritime transportation.

3.5. AI-Enhanced Navigation Systems

AI algorithms are pivotal in optimizing shipping routes, significantly boosting both safety and efficiency in maritime operations. These algorithms process extensive datasets, including real-time weather patterns, ocean currents, vessel traffic, and historical navigation routes, to determine the most efficient and safest paths for ships. By continuously updating and recalculating routes based on the latest data, AI ensures that vessels can avoid hazardous conditions such as severe weather, high-traffic areas, and navigational obstacles. Additionally, AI-driven route optimization minimizes fuel consumption by selecting the most efficient pathways, thus reducing operational costs and mitigating environmental impact. This capability not only enhances the profitability of maritime operations but also aligns with global efforts to reduce greenhouse gas emissions and promote sustainable shipping practices [58–60].

3.5.1. Implementation and Operationalization

AI systems utilize a variety of technologies and processes to optimize shipping routes. Data collection is the first step, involving sensors and other sources that gather real-time information on weather conditions, ocean currents, and vessel positions. These data are then processed by machine learning algorithms, which analyze them to identify patterns and predict future conditions. The AI system evaluates multiple potential routes, considering factors such as distance, fuel consumption, and safety risks. It then ranks these routes based on efficiency and safety criteria, providing recommendations to the ship's navigational team.

For example, the Wärtsilä FOS (Fleet Operations Solution) integrates real-time data from various sources to provide dynamic route optimization. This system uses machine learning algorithms to continuously update and optimize routes based on changing conditions, helping vessels avoid adverse weather and optimize fuel consumption. By analyzing historical and real-time data, Wärtsilä FOS can suggest the most efficient and safe routes, significantly improving operational efficiency and safety [59,60].

3.5.2. Collision Detection and Avoidance

AI systems are essential for real-time collision detection and avoidance, significantly enhancing navigational safety. These systems integrate data from radar, Automatic Identification Systems (AIS), and other advanced sensors to maintain a comprehensive and

up-to-date awareness of the vessel's surroundings. Sophisticated machine learning algorithms analyze these data to identify potential collision risks with other vessels or obstacles. Upon detecting a potential collision, the AI system provides immediate alerts and suggests evasive maneuvers to the crew. This capability is particularly critical in congested waterways and during complex maneuvers in ports. By enabling timely and informed decision-making, AI-driven collision avoidance systems help prevent accidents, ensuring the safety of the vessel, its crew, and its cargo [13,14,44,61].

With the increasing availability of maritime traffic data from the Internet of Things (IoT), deep learning is also being used for vessel trajectory prediction. The analyses address topics such as auxiliary techniques, complexity analysis, benchmarking, performance evaluation, and performance improvement in vessel trajectory prediction research [62–64].

3.5.3. Monitoring Environmental Conditions

AI technology is also instrumental in monitoring and responding to environmental conditions that affect navigation. These systems gather data on various environmental factors, including weather conditions, sea states, visibility, and tidal movements, all of which can significantly impact a vessel's route and operational safety. AI algorithms analyze these data to predict adverse environmental conditions and recommend necessary adjustments to the ship's course or speed. For instance, if severe weather is forecast along the planned route, the AI system can suggest alternative paths to avoid the storm. This proactive approach enables vessels to navigate safely through challenging environments, reducing the risk of weather-related accidents and ensuring timely arrivals. Furthermore, by continuously adapting to changing environmental conditions, AI enhances operational resilience and contributes to the overall reliability of maritime transportation [13,14,64].

The capabilities of AI in improving traffic efficiency and reducing accidents have also been recognized as a means to restore visually degraded images from video cameras during restricted visibility due to fog in the observed area. The research proposes a contrastive learning framework to enhance visibility under foggy conditions in intelligent maritime transportation systems. Specifically, the proposed learning method can fully learn both local and global image features, which positively impacts visual quality improvement. A total of 100 clear images depicting water traffic scenes were selected as the synthetic test dataset, and good dehazing results were achieved both visually and in terms of metrics. The enhanced images can be effectively utilized to promote the accuracy and robustness of ship detection. Consequently, maritime traffic supervision and management can be improved in the intelligent transportation system [65].

3.5.4. Critical Assessment of AI in Navigation

While the introduction of AI is associated with many benefits for the maritime sector, it also comes with several challenges that need to be taken into account to ensure the success of the process. Technologies using artificial intelligence collect and analyze large amounts of sensitive data, which raises privacy and security concerns. The controversial issues surrounding the implementation of AI in maritime transport include, but are not limited to:

1. **Cybersecurity:** with the digitalization of shipping and increased connectivity between ships, artificial intelligence systems, and autonomous machines, there is a greater risk associated with cybersecurity. Hackers can steal confidential information, cut off a vessel's external communications, or tamper with navigation systems, potentially causing damage to the crew, ship, and entire company by:
 - Changing vessel parameters—e.g., position, speed, name, cargo, and route information. This is an extremely dangerous phenomenon that can lead to chaos on shipping routes, causing loss of life and environmental disasters. The manipulation of the ship's parameters and the possible negative consequences of this act can be used to commit a terrorist attack.
 - Removal of existing vessels from radar—a very dangerous situation that may cause a collision between two or even more vessels, endangering human life

and the environment. Particularly dangerous in conditions of restricted visibility, where ships rely mainly on radar data.

- Creating ‘ghost ships’—recognized by other ships as real but not existing in reality. This can force navigators to make unintended course and speed alterations, creating chaos on the fairway.
- Manipulating data and images in the Electronic Chart Display and Information System (ECDIS)—this is used for voyage planning and monitoring. This system displays digital nautical charts, which are the main source of information for modern navigators. As per IMO guidelines, the ECDIS replaces paper nautical charts, which are no longer required on board. This means that altering the data in this system robs navigators of crucial information about the ship’s position and its orientation relative to navigational and land hazards.
- Sending false weather information—causing vessels to alter course to avoid non-existent adverse weather conditions or deleting information about actual bad weather and deliberately steering the ship into a storm or cyclone, which could potentially lead to its sinking.
- Installing malware in a ship’s loading and stability software—this can have catastrophic consequences. A ship that is incorrectly loaded and does not meet stability requirements can capsize, break due to hull overload, or even sink. Improperly segregated and unseparated hazardous cargo can lead to explosions and fires, causing total loss of ship and crew and severe environmental contamination.
- Falsifying distress signals by imitating emergency Position-Indicating Radio Beacons (EPIRBs) and Search and Rescue Transponders (SARTs)—this can have serious consequences. False signals from emergency beacons would particularly impact Mission Rescue Coordination Centers (MRCCs) and Search and Rescue (SAR) centers, leading to costly rescue operations and dispatching units to a non-existent threat. False signals from radar transponders would result in other vessels searching for non-existent lifeboats with potential survivors.
- There are obviously privacy regulations that hold companies responsible for how they collect, store, and use sensitive data. On the other hand, companies often lack knowledge and certainty about how their use of AI-based solutions will affect compliance with these regulations.

The potential harm of a cyberattack in maritime transport was illustrated by the Danish company Maersk in 2017. After being struck by the Petya virus, the company estimated its losses at around \$300 million [66].

2. Data integration.

Integrating new tools that use AI with the company’s and ship’s existing IT systems can be technically challenging and require significant resources, infrastructure reconfiguration, and the hiring of skilled professionals who understand both the technical aspects of AI and its application in specific maritime contexts. Lack of expertise can be a major barrier to AI implementation. The team assigned to this must understand the specific needs of maritime transport and create, train, and maintain artificial intelligence models and integrate AI tools into the ship’s existing software.

Initiatives involving multiple service providers and supply chains require all parties to be open to sharing data and interfaces. Although such collaborative projects often hold significant potential for optimization for all involved, persuading third parties to share their data can be a challenging task.

3. Difficulty in demonstrating business benefits.

Another complication standing in the way of implementing AI on ships is the difficulty in estimating and demonstrating the value of a project with AI technologies developing so rapidly. There are difficulties in deciding where and how to integrate AI into existing processes without knowing in which area the potential for benefit is greatest.

The lack of this knowledge can be due to a variety of factors, such as insufficient knowledge of AI capabilities, challenges in identifying the best ways to use it, or uncertainty about the potential benefits.

4. Concerns about employment security.

The emergence of AI often raises concerns about job displacement due to technology, particularly with robots and autonomous systems. This can create feelings of anxiety and fear among seafarers as well. Moreover, in extreme cases, this anxiety may manifest as deliberate undermining of AI programs or reluctance to adopt this technology.

While AI offers substantial benefits in navigation, its role as a primary decision-maker must be critically assessed. One significant challenge is the reliability of AI predictions, which depend on the quality and completeness of the input data. Inaccurate or incomplete data can lead to suboptimal routing decisions, potentially compromising safety. Moreover, the maritime industry has traditionally relied on human expertise and judgment, and a sudden shift to AI-driven decision-making may face resistance from seafarers and other stakeholders [67,68].

Successful integration of AI-enhanced navigation systems requires not only technological advancements but also a shift in mindset among seafarers and maritime operators. Training and familiarization programs are essential to ensure that seafarers are comfortable with using AI systems and can interpret and act on AI-generated recommendations effectively [69,70].

Despite AI's significant potential, the challenges associated with its implementation on maritime vessels underscore that human oversight will remain essential for all maritime operations. Human expertise, intuition, and the ability to visually and audibly assess the environment around the ship are currently beyond the capabilities of AI and are crucial for ensuring effective operation and safety.

3.5.5. Auxiliary Infrastructure

The implementation of AI-enhanced navigation systems also necessitates substantial auxiliary infrastructure. This includes robust data collection and transmission capabilities, as well as the power and computational resources required to process large datasets and run complex AI algorithms. Ensuring reliable connectivity in remote maritime environments is crucial for real-time data transmission and decision-making [71–73]. Moreover, the power requirements for AI systems can be significant, especially for real-time data processing and analysis. Vessels must be equipped with adequate power generation and management systems to support the continuous operation of AI-enhanced navigation systems. Additionally, integrating these systems with existing onboard equipment and ensuring compatibility with legacy systems can pose technical challenges [74].

3.5.6. Case Study

Case Study: ABB Ability™ Marine Pilot Vision

ABB's Marine Pilot Vision system represents a significant advancement in AI-driven navigation, enhancing situational awareness and overall navigation safety. The system employs a suite of sensors and sophisticated AI algorithms to construct a comprehensive 3D model of the vessel's surroundings. This high-resolution model enables advanced collision avoidance capabilities. For example, during a particularly complex maneuver in a congested port, the AI system provided real-time, precise guidance to the crew. This assistance helped the crew avoid potential collisions with other ships and port infrastructure, showcasing the system's ability to enhance navigational precision and safety in challenging environments. The successful implementation of this system across several vessels highlights its reliability and effectiveness [75].

AI-enhanced navigation systems facilitate maritime safety and efficiency. By leveraging advanced algorithms and real-time data, these systems optimize routes, detect and

avoid collisions, and monitor environmental conditions, ensuring safer and more efficient maritime operations.

3.6. AI in Energy Efficiency

Improving energy efficiency is among the strategic plans of most shipping companies. The benefits include a reduction in fuel costs and protection of the environment.

Already small changes in operating conditions can lead to substantial changes in energy consumption, making it important to continuously optimize all operations onboard a ship. As much as 25% of fuel consumption can be saved by sustainable energy consumption and optimal navigation.

Modeling fuel consumption for ships, which has a significant impact on the environment and operational costs, is a crucial challenge. The study shows that machine learning methods, such as Random Forest and Tweedie models, can effectively predict fuel consumption for ships. These findings highlight the potential applications of artificial intelligence and machine learning in maritime environment management and transportation. Advanced data analysis enables decision-makers to more accurately track fuel consumption patterns, improve operational efficiency, and reduce environmental impact, contributing to sustainable development in the maritime sector [15].

There are plenty of potential areas for efficiency improvements in ship navigation, such as economical routing, time spent in harbor and at sea, speed optimization, continuous load output, optimal propeller pitch, engine efficiency, and optimal draught and stability. Such a wide range of variables to take into account means that high performance in vessel navigation can only be achieved if interrelations are well utilized. Taking into consideration the amount of data to be processed, AI algorithms can provide significant improvements in energy efficiency.

In recent years, there has been a significant increase in interest regarding ship routing with consideration of weather conditions. Key challenges in this area involve optimizing the route and sailing speed for a given voyage, taking into account the specific marine environmental conditions. Traditional methodologies for solving this problem included the isochrone method, dynamic programming, calculus of variations, pathfinding algorithms, and heuristics. However, the importance of artificial intelligence and machine learning has also been growing in this field [76,77].

The optimum route and improved efficiency can be achieved through the careful planning and execution of voyages. Thorough voyage planning needs time, but a number of different software tools are available for planning purposes. However, it is important to remember that the data input is performed by the users at specific geographical coordinates, and the information, such as wind direction and strength, swell, and cloud cover, is obtained from visual observation. Much of these data cannot therefore be obtained at night or in restricted visibility, which significantly reduces the reliability of the calculations.

Another significant factor to consider in energy management is the operation of the main engine and the propeller.

Optimized engine performance may incrementally improve the vessel's energy efficiency. It requires proper maintenance performed at appropriate intervals.

When planning a voyage, two speed strategies can be considered—constant power and dual speed. For the constant power strategy, it is important to maintain a consistent ME (main engine) power as much as possible. Conversely, the dual-speed strategy involves operating at low power for one segment of the journey and high power for another segment.

Choosing between these two strategies can be challenging in terms of efficiency and optimization. Estimating the average ME power is often complex due to various internal and external factors. These factors include fouling on the propeller and hull, the condition and design limitations of ME operations, sea conditions, wind strength, ocean currents, speed-restricted zones, and the ship's draft and trim [78]. All these elements play a crucial role in determining the optimal route and speed towards the intended port destination.

These minimal differences, the dynamic changes, and the subtle details unnoticeable to humans strengthen the role of AI in managing energy efficiency on a vessel.

AI is playing an increasingly important role in promoting sustainability in the maritime industry by enhancing the efficiency, safety, and sustainability of the sector. International research also highlights the urgent need to take action against climate change and marine environmental degradation [79–84]. The maritime industry can reduce its carbon footprint, reduce pollution, and improve the health of ecosystems by switching to various alternative fuels, renewable energy sources, and AI-enabled technologies.

4. Challenges and Limitations

4.1. Integration Challenges

The integration of AI systems into maritime operations has been significantly enhanced by recent developments in communication technologies, particularly 5G networks and Non-Terrestrial Networks (NTNs), including satellite-based systems. These technologies address one of the primary barriers to AI adoption in the maritime domain: the lack of reliable connectivity in remote and open-sea environments. By ensuring constant data exchange between vessels, ports, and cloud-based infrastructures, 5G enables real-time decision-making for navigation, risk management, and predictive maintenance, which were previously constrained by intermittent or low-bandwidth connections [70,80,85,86].

In addition to improving communication, IoT-enabled sensors are playing a pivotal role in transforming shipboard systems. These sensors, embedded in critical equipment, allow for real-time monitoring of the ship's operational health, environmental conditions, and fuel consumption. Coupled with edge computing, these data are processed locally on the vessel, reducing the need for high-capacity onboard servers while leveraging cloud computing to analyze complex patterns in equipment performance and navigation routes [85]. This hybrid model ensures that AI-driven decisions can be made in real time, optimizing operations even in data-constrained environments.

However, despite these advancements, the integration of modern AI systems with legacy maritime infrastructure remains a significant challenge. Many ships currently in operation were not designed with AI and IoT systems in mind. As a result, retrofitting these vessels requires considerable investment in both hardware (e.g., sensors, connectivity modules) and software (e.g., AI-compatible platforms) [87]. Moreover, the heterogeneity of existing maritime systems, which vary significantly in their design and capabilities depending on their age, purpose, and geographic area of operation, complicates this integration [87].

Cybersecurity Risks

As more maritime operations become digitized, cybersecurity has emerged as a critical concern. The reliance on real-time data streams, cloud-based decision-making platforms, and IoT-enabled systems exposes the maritime sector to potential cyberattacks. Recent studies have identified that compromised AI systems could lead to catastrophic failures, including navigational errors, unauthorized access to sensitive data, and even ship collisions [86,87].

As a result, robust cybersecurity measures must be integrated into both new and existing infrastructures. This includes encrypting data, securing IoT devices, and implementing real-time monitoring systems to detect and mitigate potential threats [88].

To address these challenges, new cybersecurity frameworks are being developed specifically for maritime operations. These include secure communication protocols for vessel-to-port data exchanges and AI-based anomaly detection systems, which can identify and neutralize suspicious activity in real time. Ensuring that these protocols are standardized across the industry is essential for creating a unified approach to maritime cybersecurity [88].

Cost and Scalability

The financial cost of upgrading maritime infrastructure to support AI integration is another key hurdle. While large shipping companies with extensive fleets may have the resources to invest in cutting-edge technologies, smaller operators may struggle to afford the necessary upgrades. As AI becomes increasingly vital for ensuring safety and operational efficiency, there is a growing need for scalable solutions that can be adapted to different vessel sizes and operational scopes [85,87].

Modular AI systems are emerging as a promising solution to this problem. These systems allow operators to implement AI technologies incrementally, starting with basic functionalities like predictive maintenance and gradually adding more complex applications such as autonomous navigation and crew resource management. This approach minimizes initial costs while allowing companies to realize immediate operational benefits, such as reduced downtime and fuel savings [87].

In summary, while recent advancements in communication technologies, IoT, and cybersecurity have greatly enhanced the integration of AI systems in maritime operations, significant challenges remain. The need to retrofit older vessels, ensure robust cybersecurity, and manage the high costs associated with upgrading infrastructure are critical issues that must be addressed to fully realize the benefits of AI in this sector. Nevertheless, the transformative potential of these technologies, especially when implemented through scalable and modular solutions, offers a path forward for creating a safer, more efficient maritime industry.

4.2. Data Quality and Availability

The effectiveness of AI applications in maritime operations is fundamentally dependent on the availability and quality of data. High-quality data are essential for training machine learning models and ensuring their ability to make accurate predictions and informed decisions. However, obtaining such data in the maritime context is fraught with challenges due to the unique and often harsh conditions of this environment [85,86].

Maritime environments are dynamic and unpredictable, which complicates consistent data collection. Vessels operate in a variety of conditions, ranging from calm seas to severe storms, and across different geographic regions with varying environmental factors. This variability can lead to inconsistencies in data collection, as sensors may not function optimally under all conditions. Sensor malfunctions are a common issue, often caused by exposure to saltwater, extreme temperatures, and mechanical vibrations. These malfunctions can result in gaps or inaccuracies in the collected data [87,88].

Moreover, data transmission in maritime operations is often hindered by connectivity issues. Vessels frequently travel through remote areas with limited or no access to reliable communication networks, making real-time data transmission challenging. This can lead to delays in data availability and reduce the timeliness of the information used for AI-driven decision-making [89].

In addition to these physical and technical challenges, there is also the problem of data heterogeneity. Maritime data are collected from a multitude of sources, including sensors, logs, and external databases, each potentially using different formats and standards. This inconsistency can complicate data integration and analysis, necessitating extensive preprocessing to harmonize the data into a usable format for AI applications [90,91].

Historical data, which is often essential for training AI models, may be incomplete or biased. Incomplete datasets can arise from sporadic data collection practices or historical limitations in technology. Bias in data can result from human errors in manual data entry or from systemic issues within the data collection processes themselves. Such biases can skew the AI models, leading to less reliable predictions and decisions [92].

Addressing these data quality and availability issues is critical for the reliable deployment of AI in the maritime industry. Efforts must be made to standardize data collection methods across the industry to ensure consistency and comparability of data. Improving sensor technology is also crucial, focusing on enhancing durability and reliability under

maritime conditions. Robust data management practices, including rigorous data validation and cleansing processes, are necessary to maintain the integrity and accuracy of the data used for AI applications [93].

Furthermore, investing in advanced data transmission technologies, such as satellite communication systems, can mitigate connectivity issues and enhance the real-time availability of data. Collaborative initiatives among industry stakeholders to create centralized data repositories and share best practices can also help improve the overall quality and accessibility of maritime data [19,94].

By addressing these challenges, the maritime industry can leverage high-quality, reliable data to fully exploit the potential of AI, leading to enhanced operational safety, efficiency, and sustainability (Table 4).

Table 4. Challenges in AI integration in maritime operations.

Challenge	Description	Potential Solutions
Integration with Legacy Systems	Compatibility issues between advanced AI technologies and existing maritime infrastructure.	Gradual upgrades, modular AI systems, and training for seamless integration [79,80]
Data Quality and Availability	Difficulty in collecting consistent and high-quality data due to harsh maritime environments and sensor malfunctions.	Standardizing data collection methods, improving sensor technology, and robust data management practices [84,86]
Regulatory Compliance	Navigating complex and varied maritime regulations that may not be up-to-date with AI advancements.	Developing international standards and guidelines, staying informed about evolving regulations, and participating in industry efforts for regulatory alignment [94–96]
Ethical Considerations	Addressing the impact of AI on employment, ensuring transparency and fairness in AI decision-making, and mitigating biases in AI systems.	Implementing retraining programs, fostering explainable AI, and establishing ethical guidelines to ensure fair and unbiased AI operations [95–98]

4.3. Regulatory and Ethical Considerations

The deployment of AI in maritime operations is subject to a complex regulatory landscape and raises several ethical considerations that must be addressed to ensure responsible and sustainable integration. Maritime regulations vary significantly by region and are often slow to adapt to the rapid advancements in AI technology. Navigating this regulatory complexity while implementing AI systems poses a significant challenge for maritime operators. Ensuring compliance with existing regulations, which may not have been designed with AI in mind, requires a nuanced understanding of both the regulatory environment and the technical capabilities of AI systems [36,96].

A key aspect of addressing regulatory challenges is the development of international standards and guidelines for the use of AI in maritime operations. These standards should encompass various aspects of AI deployment, including safety, privacy, and accountability. By establishing clear guidelines, regulatory bodies can provide a framework that ensures AI systems are implemented in a manner that prioritizes safety and protects the rights and interests of all stakeholders. Harmonizing these standards across different jurisdictions can facilitate smoother adoption and compliance, reducing the burden on maritime operators who navigate international waters [97,98].

Ethical considerations are equally critical in the deployment of AI in the maritime sector. One major ethical concern is the potential impact of AI on employment within the industry. As AI systems become more capable of performing tasks traditionally handled by humans, there is a risk that automation could reduce the demand for certain roles. This displacement of jobs necessitates a proactive approach to workforce management, including retraining and upskilling programs to help affected workers transition to new

roles within the industry. Ensuring that the benefits of AI adoption are equitably distributed is essential to maintaining social responsibility [98].

Transparency and explainability of AI decisions are also paramount. Stakeholders, including crew members, operators, and regulatory authorities, need to understand how AI systems arrive at their decisions. This transparency is crucial for building trust and ensuring that AI systems are used responsibly. Explainable AI, which focuses on making AI decision-making processes understandable to humans, can help in this regard. It ensures that AI systems do not operate as “black boxes” but rather provide clear, interpretable insights to stakeholders [95–98].

Fairness in AI operations is another ethical challenge. AI systems must be designed and trained to operate without introducing biases that could lead to unfair or discriminatory outcomes. This involves careful consideration of the data used to train AI models, as biased data can perpetuate existing inequalities and lead to biased decision-making. Implementing robust bias detection and mitigation strategies is essential to ensure that AI systems operate fairly and equitably [95–98].

Balancing innovation with regulatory compliance and ethical responsibility is crucial for the sustainable integration of AI in maritime operations. This balance can be achieved through ongoing dialogue between industry stakeholders, regulatory bodies, and technology developers. By fostering a collaborative approach, the maritime industry can navigate the complexities of AI deployment while upholding the highest standards of safety, fairness, and ethical responsibility. This proactive approach will help ensure that the transformative benefits of AI are realized in a manner that supports the long-term sustainability and resilience of maritime operations [95–98].

These challenges and limitations highlight the need for a coordinated effort among industry stakeholders, regulatory bodies, and technology developers. By addressing integration hurdles, improving data quality, and navigating the regulatory and ethical landscape, the maritime industry can fully leverage AI to enhance safety, efficiency, and sustainability.

5. Future Prospects and Recommendations

The future of AI in maritime operations is poised to bring transformative advancements that will further enhance safety, efficiency, and sustainability. Emerging technologies and innovative applications hold promise for addressing some of the current limitations and unlocking new capabilities.

One significant area of development is the enhancement of AI algorithms through increased computational power and improved machine learning techniques. As AI models become more sophisticated, their ability to process and analyze vast amounts of data will improve, leading to more accurate predictions and better decision-making. Advanced neural networks and deep learning techniques will enable AI systems to understand complex patterns and interactions within maritime data, providing deeper insights into operational risks and opportunities.

The integration of AI with other emerging technologies, such as the Internet of Things (IoT), blockchain, and 5G connectivity, will further augment its capabilities. IoT devices can provide continuous, real-time data streams from sensors placed throughout ships and maritime infrastructure, allowing for more comprehensive monitoring and quicker response times. Blockchain technology can enhance the security and transparency of data transactions, ensuring the integrity of the data used by AI systems. The widespread adoption of 5G connectivity will facilitate faster and more reliable data transmission, crucial for real-time AI applications in remote maritime environments.

Another exciting prospect is the development of autonomous vessels, which rely heavily on AI for navigation, collision avoidance, and operational management. These vessels can operate with minimal human intervention, significantly reducing the risk of human error and enhancing safety. Autonomous ships can continuously optimize their routes and operations based on real-time data, leading to substantial fuel savings and emission reductions (Table 5).

Table 5. Future prospects of AI in maritime operations.

Future Development	Description	Potential Impact
Enhanced Machine Learning Algorithms	Development of more sophisticated AI models capable of deeper analysis and more accurate predictions.	Improved decision-making and operational efficiency [62,63]
Integration with IoT and Blockchain	Combining AI with IoT for real-time data collection and blockchain for secure data transactions.	Increased data reliability and operational transparency [66–68]
Autonomous Vessels	AI-driven autonomous ships capable of operating with minimal human intervention.	Significant reduction in human error, enhanced safety, and operational efficiency [79,80]
Advanced Predictive Maintenance	Improved predictive maintenance systems using advanced AI and sensor technologies.	Reduced maintenance costs and downtime, extended equipment lifespan [85,86]
Real-Time Environmental Monitoring	AI systems providing real-time analysis of environmental conditions for better navigation and operational decisions.	Enhanced safety and reduced environmental impact [74,75]

Recommendations for Implementation

To successfully implement AI systems in maritime operations, several best practices should be followed:

1. Stakeholder Collaboration: Effective AI implementation requires collaboration among various stakeholders, including shipowners, technology providers, regulatory bodies, and crew members. Engaging all relevant parties ensures that AI solutions are designed and deployed in a manner that addresses the practical needs and regulatory requirements of the maritime industry.
2. Comprehensive Training and Education: Ensuring that personnel are adequately trained to use and interact with AI systems is crucial. Training programs should focus on enhancing the digital literacy of the maritime workforce, equipping them with the skills needed to operate AI tools and interpret their outputs. Continuous education initiatives can help keep the workforce updated on the latest AI developments and best practices.
3. Robust Data Management: The foundation of effective AI applications lies in high-quality data. Establishing robust data management practices, including standardized data collection methods, rigorous data validation processes, and secure data storage solutions, is essential. Investing in advanced sensor technologies and reliable data transmission systems can help overcome data quality and availability challenges.
4. Incremental Integration: Rather than attempting a full-scale AI implementation all at once, a phased approach can be more effective. Starting with pilot projects and gradually scaling up allows organizations to identify and address potential issues early on in the process. This incremental integration can help build confidence in AI systems and ensure smoother adoption.
5. Regulatory Compliance and Ethical Considerations: Adhering to regulatory requirements and addressing ethical considerations are paramount for sustainable AI deployment. Organizations should stay informed about evolving regulations and actively participate in industry efforts to develop international standards for AI use in maritime operations. Ethical guidelines should be established to ensure transparency, fairness, and accountability in AI systems.
6. Continuous Monitoring and Improvement: AI systems should be continuously monitored to assess their performance and identify areas for improvement. Implementing feedback loops where insights from real-world operations are used to refine AI models can enhance their accuracy and reliability over time. Regular audits and evaluations can help ensure that AI systems remain aligned with safety standards and operational goals.

By embracing these recommendations and staying abreast of technological advancements, the maritime industry can leverage AI to significantly enhance safety, efficiency, and sustainability. The future of maritime operations, empowered by AI, holds the potential for safer seas and more efficient global trade.

6. Conclusions

The integration of AI in maritime transportation holds immense potential for enhancing safety, efficiency, and sustainability within the industry. This research has explored various AI applications, demonstrating significant improvements in operational safety and efficiency through AI-driven risk analysis, seafarer resource management, hazardous material handling, predictive maintenance, and navigation systems.

Key findings include the successful implementation of AI technologies such as Wärtsilä's Fleet Operations Solution, ABB's Marine Pilot Vision, and Kongsberg's Kognifai Maritime Ecosystem. These case studies highlight AI's ability to optimize routes, prevent collisions, and monitor environmental conditions effectively, thereby enhancing the operational performance and safety of maritime operations.

However, several challenges remain, including the integration of AI systems with existing maritime infrastructure, ensuring data quality and availability, and navigating the complex regulatory and ethical landscape. Addressing these hurdles requires a collaborative effort among industry stakeholders, regulatory bodies, and technology providers. Establishing robust data management practices, adhering to regulatory standards, and addressing ethical considerations are essential steps toward the responsible deployment of AI in maritime operations.

Looking ahead, advancements in AI technology, such as enhanced machine learning algorithms, integration with IoT and blockchain, and the development of autonomous vessels, promise to further revolutionize the maritime industry. Future research should focus on overcoming the technical and operational challenges identified, exploring the implications of increased AI autonomy, and ensuring that the human workforce is adequately trained and integrated into this technological evolution.

While the future of maritime transportation empowered by AI is promising, it is essential to balance this optimism with a realistic assessment of the challenges ahead. By leveraging AI's transformative potential and addressing its limitations through continuous research and collaboration, the maritime industry can achieve safer, more efficient, and sustainable operations. This comprehensive approach will not only enhance the resilience and reliability of maritime transportation but also contribute significantly to the broader goal of sustainable global trade and economic growth.

This review not only synthesizes the current state of AI applications in maritime safety but also provides a roadmap for future research and development. By addressing the key challenges of infrastructure compatibility, regulatory frameworks, and data quality, the maritime industry can fully leverage the transformative potential of AI. Future studies should focus on improving interoperability between AI systems and legacy maritime infrastructure, as well as developing international standards that ensure safe and ethical AI integration.

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