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| RESEARCH ARTICLE

Artificial Intelligence in Maritime Operations: A Systematic Review of Smart Shipping, Port Automation, and Decision Support Systems

Samuel Odupe
University of Lagos, Nigeria
Corresponding Author: Samuel Odupe, **E-mail**: odupesamuel@gmail.com

| ABSTRACT
Artificial Intelligence (AI) is increasingly reshaping maritime operations by enabling intelligent decision-making, enhancing operational efficiency, and supporting the transition toward smart and autonomous shipping systems. This study presents a systematic review of the application of AI in maritime operations, with a specific focus on smart shipping, port automation, and decision support systems. Drawing on a wide range of peer-reviewed literature, industry reports, and case-based evidence, the review synthesizes current developments, key technologies, and implementation outcomes across the maritime value chain. The findings indicate that AI-driven systems such as machine learning algorithms, computer vision, predictive analytics, and autonomous control systems are significantly improving vessel navigation, fuel optimization, predictive maintenance, and cargo handling efficiency. In port operations, AI-enabled automation is streamlining container handling, traffic management, and resource allocation, thereby reducing turnaround times and operational costs. Furthermore, AI-based decision support systems are enhancing situational awareness, risk assessment, and strategic planning for maritime stakeholders. However, the study also identifies persistent challenges, including data interoperability issues, cybersecurity risks, high implementation costs, regulatory uncertainty, and limited digital infrastructure in developing regions. Despite these barriers, the review highlights strong momentum toward AI integration, driven by Industry 4.0 advancements and increasing demand for sustainable and efficient maritime logistics. The study concludes that AI holds transformative potential for maritime operations, but its full benefits can only be realized through improved governance frameworks, standardized data systems, and increased investment in digital capabilities across global shipping and port ecosystems.

| KEYWORDS

Maritime operations, Artificial Intelligence, cybersecurity, traffic management, container handling.

| ARTICLE INFORMATION

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1. Introduction

The maritime industry forms the backbone of global trade, facilitating the movement of approximately 80% of international goods by volume. In recent years, this sector has undergone a profound technological transformation driven by digitalization, connectivity, and data-driven systems. Among the most disruptive innovations is Artificial Intelligence (AI), which is increasingly reshaping maritime operations through applications in smart shipping, port automation, predictive analytics, and advanced decision support systems (Liu, 2025). These developments are redefining traditional maritime practices by enhancing efficiency, safety, sustainability, and operational resilience across the global maritime supply chain.

Artificial Intelligence, broadly defined as the simulation of human intelligence processes by machines particularly computer systems has found expanding relevance in maritime contexts. Its capabilities in machine learning, computer vision, natural language processing, and autonomous decision-making are being integrated into vessel navigation, cargo handling, fleet optimization, and port logistics. Smart shipping, for instance, leverages AI-enabled autonomous navigation systems and predictive maintenance tools to reduce human error, optimize fuel consumption, and improve voyage efficiency (Zou, 2025). Similarly, port automation systems are increasingly relying on AI-driven algorithms to streamline container handling, traffic management, and berth allocation, thereby minimizing congestion and turnaround times.

The growing adoption of AI in maritime operations is also closely aligned with broader global efforts to enhance sustainability and reduce carbon emissions in shipping activities. International regulatory bodies, particularly the International Maritime Organization, have emphasized the importance of digital transformation and innovation in achieving decarbonization targets and improving maritime safety standards (Tahir, 2024). In this context, AI technologies are not only operational tools but also strategic enablers supporting compliance with environmental regulations and the transition toward greener shipping practices.

Despite these advancements, the integration of AI into maritime systems remains uneven and complex. Challenges such as data interoperability, cybersecurity risks, high implementation costs, and regulatory uncertainty continue to hinder widespread adoption. Moreover, the effectiveness of AI-driven decision support systems depends heavily on the quality, availability, and integration of maritime data sources, which are often fragmented across stakeholders such as shipping companies, port authorities, and logistics providers (Paraskevas, 2024). These limitations highlight the need for a comprehensive synthesis of existing research to better understand both the opportunities and constraints associated with AI deployment in maritime environments.

This study therefore presents a systematic review of Artificial Intelligence applications in maritime operations, with a particular focus on smart shipping, port automation, and decision support systems. By consolidating findings from recent academic and industry literature, the review aims to identify key technological trends, evaluate operational impacts, and highlight existing gaps in knowledge and practice (Xiao, 2024). Ultimately, the study contributes to a deeper understanding of how AI is transforming maritime operations and provides insights into future research directions and policy considerations for sustainable and intelligent maritime systems.

2. Methodology

2.1 Research Design

This study adopts a systematic review design to critically examine and synthesize existing literature on Artificial Intelligence (AI) applications in maritime operations, with a specific focus on smart shipping, port automation, and decision support systems. A systematic review approach was selected due to its rigor, transparency, and replicability in identifying, evaluating, and synthesizing relevant scholarly evidence. The methodology is grounded in established systematic review principles, ensuring that the findings are comprehensive and representative of the current state of research in AI-driven maritime transformation.

2.2 Search Strategy and Data Sources

The literature search was conducted across multiple academic databases to ensure broad coverage of relevant studies. Key databases included Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The search strategy combined keywords and Boolean operators such as “Artificial Intelligence” AND “maritime operations,” “smart shipping,” “port automation,” “intelligent shipping systems,” and “AI-based decision support in logistics.” The search was limited to peer-reviewed journal articles, conference proceedings, and high-impact review papers published in English to maintain academic quality and relevance. The time frame was defined to capture both foundational and recent advancements in AI applications within maritime contexts.

2.3 Inclusion and Exclusion Criteria

Studies were included if they directly addressed the application of AI technologies in maritime operations, including shipping, port management, vessel navigation, logistics optimization, and decision support systems. Eligible studies were required to present empirical findings, theoretical frameworks, or systematic analyses relevant to AI deployment in maritime environments. Exclusion criteria involved studies that focused solely on general logistics without maritime specificity, non-peer-reviewed sources, opinion pieces without methodological rigor, and publications not available in English. Duplicate records and studies lacking sufficient methodological detail were also excluded to maintain the integrity of the synthesis.

2.4 Study Selection Process

The study selection process followed a structured screening approach consistent with systematic review protocols. Initially, all identified records were imported into a reference management system, and duplicates were removed. Titles and abstracts were then screened to assess relevance to the research objectives. Full-text articles were subsequently reviewed for eligibility based on the predefined inclusion and exclusion criteria. This multi-stage screening process ensured that only studies with direct relevance to AI applications in maritime operations were included in the final synthesis, thereby enhancing the reliability and validity of the review outcomes.

2.5 Data Extraction and Coding

Data extraction was conducted using a structured framework to ensure consistency and comparability across studies. Key information extracted included author details, publication year, research objectives, AI methodologies employed, application domains (smart shipping, port automation, or decision support systems), datasets used, and principal findings. The extracted data were then systematically coded to identify recurring themes, technological trends, and application patterns. This coding process enabled the categorization of studies into analytically meaningful groups that align with the objectives of the review.

2.6 Quality Assessment

To ensure the credibility of the included studies, a quality assessment was performed using established evaluation criteria for methodological rigor, clarity of objectives, robustness of data analysis, and validity of findings. Each study was assessed in terms of research design appropriateness, transparency of AI model implementation, and reliability of reported outcomes. Studies with insufficient methodological clarity or weak empirical grounding were given lower weight in the synthesis process. This step helped minimize bias and ensured that the conclusions drawn were based on high-quality evidence.

2.7 Data Synthesis and Analysis

The synthesized data were analyzed using a thematic synthesis approach, enabling the identification of key patterns, trends, and gaps in the literature. Findings were organized around the core thematic areas of smart shipping, port automation, and AI-enabled decision support systems. Comparative analysis was conducted to highlight convergences and divergences in methodologies, technologies, and application outcomes across studies. The synthesis also facilitated the identification of emerging trends, such as the integration of machine learning, predictive analytics, and autonomous systems in maritime operations. This analytical approach provided a coherent and structured understanding of the evolving role of AI in transforming maritime systems.

3. Findings and Discussion

3.1 AI in Smart Shipping Operations

The systematic review reveals that artificial intelligence is increasingly embedded in smart shipping operations, particularly in navigation autonomy, predictive maintenance, and fuel efficiency optimization. Across the reviewed studies, a consistent trend emerges: AI technologies are transitioning maritime operations from reactive, human-dependent decision-making toward proactive, data-driven, and semi-autonomous systems. However, the extent of adoption varies significantly between experimental deployments, pilot projects, and limited commercial implementations (Belmoukari, 2023). While fully autonomous vessels remain largely in testing phases, semi-autonomous systems integrated with AI-based decision support are already demonstrating measurable operational benefits in real-world maritime environments.

3.1.1 Autonomous Navigation Systems

Findings from the reviewed literature indicate that AI-enabled autonomous navigation systems are primarily designed to enhance situational awareness, improve collision avoidance, and optimize route selection using real-time environmental and vessel data. These systems typically integrate sensor fusion technologies such as radar, LiDAR, Automatic Identification System (AIS), and computer vision algorithms to interpret dynamic maritime conditions (Jimoh, 2023). Studies consistently show that machine learning and deep reinforcement learning models outperform traditional rule-based navigation systems in complex and congested shipping lanes, particularly in scenarios involving high traffic density or poor visibility.

A key finding is the clear stratification of autonomy levels in maritime operations. Most operational systems currently fall within Level 2 to Level 3 autonomy (semi-autonomous), where AI supports navigation decisions but human officers remain in control. Fully autonomous (Level 4–5) ships are still largely experimental, with notable examples such as the Yara Birkeland project illustrating the feasibility of autonomous short-sea shipping (Munim, 2020). Evidence suggests that semi-autonomous systems can reduce navigational errors and improve route efficiency by up to 10–20%, particularly through dynamic rerouting based on weather and ocean current predictions.

Previous studies, including those aligned with the International Maritime Organization's digital shipping frameworks, emphasize that while AI improves operational precision, regulatory uncertainty and cybersecurity risks remain major barriers to full autonomy (Riyadh, 2024). The review confirms these concerns, noting that most deployments prioritize decision-support augmentation rather than full automation, ensuring compliance with COLREGs and human oversight requirements.

3.1.2 Predictive Maintenance and Vessel Monitoring

The reviewed studies strongly indicate that predictive maintenance powered by AI is one of the most mature applications in maritime operations. Machine learning algorithms, particularly supervised learning models and neural networks, are widely used to analyze sensor data from ship engines, propulsion systems, and structural components (Hirata, 2024). These systems detect anomalies and predict equipment failures before they occur, enabling condition-based maintenance strategies instead of traditional scheduled maintenance.

A recurring finding across multiple studies is the significant reduction in operational downtime and maintenance costs. Predictive maintenance systems have been shown to reduce unplanned engine failures by approximately 20–40%, while extending equipment lifecycle through optimized maintenance scheduling (El Saadani, 2023). For example, AI-based hull monitoring systems using ultrasonic and vibration sensors have demonstrated early detection of micro-fractures and corrosion, preventing costly structural repairs and dry-docking delays.

In comparison with earlier rule-based diagnostic systems, AI-driven approaches offer higher accuracy and adaptability, especially when dealing with large-scale heterogeneous data from Internet of Things (IoT) sensors onboard vessels (Ekwunife, n.d). Prior research by maritime engineering scholars supports these findings, emphasizing that deep learning models outperform statistical threshold-based monitoring in identifying complex fault patterns.

However, the literature also highlights challenges related to data quality, sensor calibration, and integration across legacy ship systems. These limitations often reduce the effectiveness of predictive models in older fleets, suggesting that the benefits of AI are currently more pronounced in newly built smart vessels rather than retrofitted ships (Isbaex, 2025).

3.1.3 Fuel Efficiency and Emissions Optimization

The review identifies AI-driven fuel optimization systems as a critical innovation in addressing both economic and environmental pressures in maritime transport. Machine learning algorithms, including regression models, genetic algorithms, and reinforcement learning techniques, are widely used to optimize voyage planning, engine performance, and speed management (Gonçalves, 2025). These systems analyze variables such as weather conditions, sea currents, vessel load, and port congestion to recommend optimal sailing routes and speeds.

A key finding is that AI-based voyage optimization can reduce fuel consumption by approximately 5–15% depending on vessel type and operational conditions. This directly contributes to reduced greenhouse gas emissions, supporting compliance with International Maritime Organization (IMO) regulations, including the Energy Efficiency Design Index (EEDI) and the Carbon Intensity Indicator (CII) (Mar-Ortiz, 2018). Studies also highlight that reinforcement learning models, which continuously adapt to environmental feedback, outperform traditional optimization techniques such as linear programming in dynamic maritime environments.

Comparative analysis across studies indicates that hybrid AI models combining machine learning with physics-based simulation produce more reliable results than standalone algorithms. For instance, integrating weather routing systems with neural network-based engine performance models yields more precise fuel-saving recommendations (Samuel 2021).

Previous research in maritime sustainability confirms these findings, emphasizing that AI adoption is becoming a strategic necessity rather than an optional enhancement. However, the literature also notes that operational constraints, such as charter party agreements, safety requirements, and port scheduling limitations, can restrict the full implementation of AI-optimized routes (Durlik, 2024).

3.2 AI in Port Automation Systems

The systematic review reveals that Artificial Intelligence (AI) plays a transformative role in modern port automation systems, significantly enhancing operational efficiency, reducing vessel turnaround time, and optimizing labor utilization. Across the reviewed studies, AI-enabled port systems are consistently associated with a shift from semi-automated operations to fully integrated smart port ecosystems. These developments are particularly evident in cargo handling, terminal coordination, infrastructure management, and traffic control systems, where AI is increasingly embedded within decision-making and operational workflows (Kishore, 2024). The findings align with earlier work on smart port evolution, which emphasizes digitalization and automation as key drivers of port competitiveness and resilience in global supply chains.

3.2.1 Intelligent Cargo Handling and Terminal Operations

The review indicates that intelligent cargo handling systems, particularly AI-enabled automated cranes, robotic stacking systems, and predictive cargo scheduling platforms, have significantly improved terminal productivity. Automated quay cranes equipped with machine learning algorithms are now capable of optimizing container lifting sequences based on vessel stability, cargo priority, and real-time yard conditions (Prousaloglou, 2025). In major ports such as the Port of Rotterdam and the Port of Singapore, AI-driven terminal operating systems have reduced average vessel turnaround times by streamlining loading and unloading processes and minimizing human intervention in high-risk environments.

Furthermore, robotic systems integrated with computer vision technologies are increasingly deployed in container yards to manage stacking, retrieval, and transport operations. These systems reduce dependency on manual labor while improving precision and safety. Studies reviewed consistently report efficiency gains ranging from reduced idle crane time to improved berth productivity rates (GBOLADE, 2018). This finding corroborates earlier research suggesting that automation in terminal operations not only enhances throughput but also reduces operational bottlenecks caused by human fatigue and coordination delays.

AI-based cargo scheduling systems also emerged as a critical innovation. These systems utilize predictive analytics to forecast cargo arrival patterns, optimize container placement, and dynamically allocate terminal resources. Evidence from reviewed literature suggests that such systems improve yard utilization rates and reduce container dwell time, thereby enhancing overall port performance (Madsen, 2024). However, several studies also highlight implementation challenges, including high capital investment costs and integration complexities with legacy terminal operating systems.

3.2.2 Smart Port Infrastructure and Digital Twins

The findings demonstrate that the integration of AI with Internet of Things (IoT) technologies and digital twin models is reshaping port infrastructure management. Digital twins virtual replicas of physical port environments are increasingly used to simulate real-time port operations, enabling predictive maintenance, infrastructure optimization, and scenario-based planning (Abdelsalam, 2024). Ports such as Hamburg and Shanghai have adopted digital twin frameworks to model berth utilization, equipment performance, and environmental conditions, allowing operators to anticipate system failures and optimize resource allocation.

AI enhances these digital twin systems by enabling adaptive learning from real-time sensor data collected through IoT networks. This integration allows ports to continuously refine operational models, improving accuracy in forecasting equipment wear, energy consumption, and spatial utilization (Aylak, 2022). The reviewed studies indicate that such systems contribute to reduced downtime and improved asset lifecycle management, aligning with prior research that identifies predictive maintenance as a key benefit of AI-enabled infrastructure.

Additionally, smart port infrastructure supported by AI facilitates more sustainable operations. Energy consumption optimization, emissions monitoring, and automated lighting and cooling systems are increasingly governed by AI algorithms that respond dynamically to operational demand (Safuan, 2024). These developments support global sustainability targets within maritime logistics, reinforcing earlier findings that digitalization contributes not only to efficiency but also to environmental performance improvements.

3.2.3 Port Traffic Management and Congestion Control

The review further identifies significant advancements in AI-based port traffic management systems, particularly in vessel arrival forecasting, berth allocation optimization, and congestion mitigation. Machine learning models are widely used to predict vessel arrival times with greater accuracy, allowing port authorities to proactively manage berth schedules and reduce waiting times at anchorage zones (Kosiek, 2021). This predictive capability is especially important in high-traffic ports such as Los Angeles, Rotterdam, and Shanghai, where congestion has historically led to substantial economic inefficiencies.

AI-driven berth allocation systems were found to improve decision-making by dynamically assigning docking spaces based on vessel size, cargo type, priority status, and real-time port conditions. These systems outperform traditional rule-based allocation methods by incorporating stochastic variables such as weather conditions, tidal variations, and unexpected delays (Durlik, 2024). As a result, ports experience improved throughput and reduced demurrage costs, which is consistent with prior studies emphasizing the economic benefits of intelligent scheduling systems in maritime logistics.

Congestion control mechanisms also benefit from AI-enabled simulation tools that model port traffic flow and identify potential bottlenecks before they occur. These tools support strategic planning by enabling scenario testing for peak demand periods and emergency disruptions. However, the review also highlights that data interoperability and real-time information sharing remain critical challenges, particularly in ports where digital infrastructure is unevenly developed (Tsolakis, 2022). Prior research similarly notes that the effectiveness of AI in traffic management is highly dependent on data quality, system integration, and institutional coordination.

3.3 AI-Driven Decision Support Systems in Maritime Operations

Artificial Intelligence (AI)-driven decision support systems (DSS) have emerged as a central enabler of efficiency, safety, and resilience in maritime operations. Across the reviewed literature, these systems are consistently positioned as integrative tools that transform raw maritime data collected from sensors, Automatic Identification Systems (AIS), satellite feeds, and port management platforms into actionable insights for real-time and strategic decision-making (Islam, 2023). The findings indicate that AI-based DSS are increasingly embedded in navigation systems, port coordination platforms, and logistics management frameworks, supporting both operational-level decisions and long-term planning across global maritime networks.

3.3.1 Real-Time Operational Decision-Making

The reviewed studies reveal that AI-enabled real-time decision-making systems significantly enhance maritime situational awareness, particularly in navigation safety, vessel routing, and emergency response coordination. Machine learning algorithms combined with AIS and meteorological data are widely used to optimize vessel routes dynamically, reducing fuel consumption while avoiding adverse weather conditions and congested shipping lanes (Islam, 2023). For example, shipping operators such as large container fleet managers have adopted AI-based route optimization tools that continuously adjust voyage plans in response to real-time oceanographic and traffic data.

In port environments, AI-powered decision platforms assist in coordinating berth allocation, crane scheduling, and cargo handling activities. Evidence from smart port implementations such as those reported in highly automated terminals in Europe and Asia shows that real-time DSS reduce vessel waiting times and improve turnaround efficiency by synchronizing ship arrivals with terminal capacity and labor availability (Madsen, 2024). Similar findings in previous studies on smart shipping systems highlight that real-time predictive analytics improves decision speed and accuracy compared to traditional rule-based systems.

In emergency response scenarios, AI-based DSS support maritime authorities in detecting anomalies such as onboard system failures, collision risks, or distress signals. These systems integrate predictive models with real-time sensor data to recommend immediate corrective actions, such as course deviation or evacuation procedures (Samuel 2021). Prior research on maritime safety systems emphasizes that such AI-driven interventions reduce human response delays, particularly in high-traffic and high-risk sea corridors.

3.3.2 Risk Assessment and Maritime Safety Management

The findings indicate a growing application of AI in predictive risk assessment and maritime safety management, where systems are trained to identify potential hazards before they escalate into incidents. AI models leveraging historical accident data, vessel behavior patterns, and environmental conditions are increasingly used to predict collision risks, grounding events, and mechanical failures (Islam, 2025). This predictive capability represents a shift from reactive to proactive safety management in maritime operations.

Several studies highlight the use of deep learning and probabilistic models to assess piracy risks in high-risk maritime regions, particularly in parts of the Gulf of Aden and West African waters. These systems analyze historical piracy incidents, vessel routes, and socio-political indicators to generate risk heat maps that guide route planning and naval escort deployment (Liu, 2025). Similarly, weather-related disruption forecasting using AI-based meteorological models enables shipping companies to anticipate storms, cyclones, and extreme sea conditions with greater precision than traditional forecasting methods.

Compliance risk management is another area where AI-driven DSS are gaining importance. Automated monitoring systems are used to ensure adherence to International Maritime Organization (IMO) regulations, emissions standards, and safety protocols. The reviewed literature shows that AI-based compliance tools can detect irregularities in fuel usage, emissions levels, and operational procedures, thereby reducing the risk of regulatory penalties (Zou, 2025). Prior studies on maritime governance also emphasize that such systems improve transparency and accountability in fleet operations, particularly in large multinational shipping companies.

3.3.3 Supply Chain and Logistics Optimization

AI-driven DSS are also transforming maritime supply chain and logistics optimization by enhancing forecasting accuracy, inventory control, and multimodal coordination. The findings show that predictive analytics models are widely used to forecast cargo demand, enabling shipping companies and port operators to optimize vessel deployment, container allocation, and storage capacity (Tahir, 2024). These systems rely on historical trade data, seasonal demand patterns, and macroeconomic indicators to improve forecasting reliability.

In inventory and warehouse management, AI systems are integrated with port community systems to track container flows in real time, reducing dwell time and minimizing congestion. For instance, smart logistics hubs in major global ports have implemented AI-based yard management systems that optimize container stacking and retrieval processes, improving operational throughput and reducing manual handling errors (Paraskevas, 2024).

Multimodal integration is another key area of AI application, where decision support systems coordinate maritime transport with rail, road, and air freight systems. The literature indicates that AI-enabled logistics platforms facilitate end-to-end visibility across supply chains, allowing stakeholders to dynamically reroute cargo in response to disruptions such as port congestion, labor strikes, or geopolitical events (Xiao, 2024). Previous studies on global supply chain resilience similarly highlight that AI-based optimization improves adaptability and reduces operational bottlenecks, particularly in just-in-time logistics environments.

3.4 Barriers and Challenges in AI Adoption

3.4.1 Technological Limitations and Data Quality Issues

The review findings indicate that technological constraints remain one of the most persistent barriers to the effective adoption of artificial intelligence in maritime operations. A key challenge relates to the lack of high-quality, standardized, and interoperable datasets across shipping lines, ports, and logistics service providers. Many AI applications in smart shipping and port automation rely heavily on heterogeneous data sources such as Automatic Identification System (AIS) data, Electronic Data Interchange (EDI) records, terminal operating systems (TOS), and sensor-based Internet of Things (IoT) devices (Belmoukari, 2023). However, inconsistencies in data formats, missing values, and limited historical depth significantly reduce model accuracy and reliability. For instance, predictive analytics systems designed for vessel arrival time estimation often struggle with incomplete AIS signals in congested maritime corridors or regions with weak satellite coverage.

In addition, interoperability issues between legacy maritime information systems and emerging AI-driven platforms hinder seamless integration. Many ports and shipping companies continue to operate fragmented digital infrastructures that were not designed for real-time data exchange or machine learning integration. Previous studies on digital transformation in maritime logistics have similarly highlighted that siloed systems restrict the scalability of AI solutions, particularly in multi-stakeholder environments such as port community systems (Jimoh, 2023). Furthermore, integration challenges are exacerbated by cybersecurity concerns, where organizations limit data sharing due to fears of exposure to cyber threats, thereby constraining the volume and diversity of datasets required for robust AI training and deployment.

3.4.2 Regulatory, Legal, and Ethical Constraints

The findings also reveal that regulatory and legal uncertainty constitutes a significant barrier to AI adoption in maritime operations, particularly in the context of autonomous shipping and AI-driven decision-support systems. Although organizations such as the International Maritime Organization (IMO) have initiated discussions on Maritime Autonomous Surface Ships (MASS), the current international regulatory framework remains largely designed for conventional crewed vessels (Munim, 2020). This regulatory gap creates uncertainty regarding certification standards, operational accountability, and compliance requirements for AI-enabled maritime systems.

A major concern identified in the literature is liability attribution in the event of AI system failure. For example, if an autonomous navigation system contributes to a collision or grounding incident, ambiguity arises regarding whether responsibility lies with the shipowner, software developer, system integrator, or AI algorithm itself. Previous legal analyses in maritime law have consistently emphasized that existing conventions such as SOLAS and COLREGS do not adequately address machine decision-making autonomy, thereby complicating insurance underwriting and risk allocation (Riyadh, 2024).

Ethical concerns also emerge in relation to AI-driven decision-making in safety-critical scenarios. AI systems used for collision avoidance, route optimization, and cargo prioritization may be required to make real-time trade-offs that have ethical implications, particularly in emergency situations. Scholars have raised concerns that algorithmic decision-making may lack transparency and explainability, making it difficult for human operators to fully understand or challenge system outputs (Hirata, 2024). This raises broader questions about trust, accountability, and the acceptable level of autonomy in maritime operations, especially when human lives, environmental safety, and high-value cargo are involved.

3.4.3 Organizational and Human Resource Constraints

The review further identifies organizational resistance and human resource limitations as critical challenges affecting AI implementation in maritime organizations. Many shipping companies and port authorities exhibit institutional inertia, where established operational practices and hierarchical decision-making structures slow the adoption of disruptive technologies such as AI (El Saadani, 2023). Resistance to change is often driven by uncertainty regarding return on investment, fear of job displacement, and limited organizational readiness for digital transformation.

A significant skills gap was also observed across the maritime workforce. The deployment of AI-based systems such as predictive maintenance tools, intelligent port scheduling systems, and autonomous navigation platforms requires advanced competencies in data analytics, machine learning interpretation, and systems integration. However, many maritime professionals, particularly seafarers and port operational staff, lack formal training in these areas (Ekwunife, n.d). This skills mismatch has been highlighted in previous studies as a major constraint to digitalization in the maritime sector, where traditional maritime education and training curricula have not kept pace with emerging technological demands.

Furthermore, inadequate training and change management strategies hinder effective human–machine collaboration. In several documented cases, AI systems introduced in port operations were underutilized or overridden due to lack of user trust or insufficient understanding of system logic. This indicates that successful AI adoption requires not only technological investment but also continuous capacity building, re-skilling programs, and organizational culture shifts that support innovation (Isbaex, 2025). Without such interventions, the potential efficiency gains from AI-enabled maritime systems risk being significantly under-realized.

3.5 Future Prospects and Emerging Trends in AI-Driven Maritime Operations

The review of literature indicates that artificial intelligence in maritime operations is entering a transformative phase characterized by convergence with complementary digital technologies, increased autonomy, and sustainability-driven innovation. Across the analyzed studies, there is broad agreement that the next generation of smart shipping and port systems will not evolve in isolation but through integrated ecosystems that combine AI with distributed data infrastructures and advanced automation frameworks (Gonçalves, 2025). These emerging trends collectively point toward a maritime sector that is more interconnected, predictive, and environmentally responsive than current operational models.

3.5.1 Integration of AI with Blockchain and IoT

Findings from the reviewed studies consistently show that the convergence of artificial intelligence with blockchain and the Internet of Things (IoT) is increasingly viewed as a foundational development in maritime digital transformation. IoT-enabled sensors installed on vessels, cargo containers, and port infrastructure generate continuous real-time data on parameters such as location, temperature, fuel consumption, and structural integrity. AI systems then analyze this data to optimize routing, predict maintenance needs, and enhance decision-making processes (Mar-Ortiz, 2018). Blockchain technology complements this ecosystem by providing a secure, immutable ledger for recording transactions and operational events, thereby enhancing trust and accountability among stakeholders.

For example, several studies highlight that combining AI-based predictive analytics with blockchain-based documentation systems significantly reduces cargo fraud, documentation errors, and customs clearance delays. Similar findings are reported in earlier work by scholars who emphasize that digital twins of shipping operations become more reliable when IoT data streams are validated through blockchain frameworks, ensuring data integrity across supply chain nodes (Samuel 2021). This integration is also seen as particularly valuable in reducing inefficiencies in global trade documentation processes, where paper-based systems have historically created bottlenecks and opportunities for manipulation.

However, the literature also reveals persistent challenges, including interoperability issues between heterogeneous IoT devices and blockchain platforms, as well as the computational costs associated with large-scale real-time data validation (Durlik, 2024). Despite these limitations, the consensus across studies is that the integration of AI, IoT, and blockchain represents a critical step toward fully transparent, traceable, and autonomous maritime ecosystems.

3.5.2 Advancements in Fully Autonomous Shipping

The reviewed evidence indicates rapid progress toward fully autonomous shipping, driven by advancements in machine learning, computer vision, sensor fusion, and remote operation technologies. A significant proportion of studies discuss the development of unmanned surface vessels (USVs) and autonomous cargo ships capable of navigating complex maritime environments with minimal or no human intervention (Kishore, 2024). These vessels rely on AI-powered navigation systems that integrate radar, lidar, GPS, and satellite data to make real-time operational decisions, including collision avoidance, route optimization, and weather adaptation.

Empirical examples from pilot projects in Europe and Asia demonstrate that semi-autonomous vessels have already achieved operational success in controlled environments, particularly in short-sea shipping and inland waterways. Remote operation centers, often referred to as “shore control hubs,” are increasingly being deployed to monitor and intervene in vessel operations when necessary (Prousaloglou, 2025). This hybrid model reflects a transitional phase toward full autonomy, aligning with findings from previous studies that emphasize incremental automation rather than abrupt replacement of human crews.

Despite technological progress, regulatory and ethical readiness remains a key constraint. International maritime law, particularly frameworks governed by the International Maritime Organization (IMO), is still evolving to accommodate autonomous vessels. Issues such as liability in the event of accidents, cybersecurity risks, and decision accountability remain unresolved (GBOLADE, 2018). The literature therefore suggests that while technological capability is advancing rapidly, institutional and legal frameworks are lagging behind, creating a governance gap that must be addressed before large-scale deployment becomes feasible.

3.5.3 Sustainable and Green Maritime AI Solutions

A major emerging trend identified in the review is the increasing application of AI to support decarbonization and environmental sustainability in maritime operations. Studies consistently show that shipping, as a major contributor to global greenhouse gas emissions, is under growing regulatory and economic pressure to adopt greener technologies (Madsen, 2024). AI-driven systems are being used to optimize fuel consumption, reduce emissions, and improve energy efficiency through intelligent voyage planning, slow steaming strategies, and real-time engine performance monitoring.

For instance, AI-based route optimization systems that incorporate meteorological and oceanographic data have been shown to significantly reduce fuel usage by recommending energy-efficient navigation paths. These findings align with earlier research emphasizing the role of predictive analytics in minimizing operational inefficiencies and carbon intensity in maritime logistics (Abdelsalam, 2024). Additionally, machine learning models are increasingly being integrated into port operations to reduce vessel waiting times at anchorage, thereby lowering unnecessary fuel burn during idle periods.

The review also identifies growing interest in AI-enabled hybrid propulsion systems and integration with alternative fuels such as LNG, hydrogen, and ammonia. AI plays a critical role in monitoring fuel performance and ensuring safety in these emerging energy systems (Aylak, 2022). Furthermore, climate-resilient shipping operations are being enhanced through AI-powered weather forecasting and risk assessment tools that enable proactive avoidance of extreme weather events, reducing both environmental and economic losses.

However, the adoption of sustainable AI solutions is not without challenges. High implementation costs, data availability constraints, and uneven technological readiness across global ports create disparities in adoption rates (Safuan, 2024). Nonetheless, the overall trajectory of the literature suggests that sustainability-oriented AI innovations will become central to future maritime competitiveness, particularly as global regulatory regimes tighten emissions standards.

4. Conclusion

This systematic review has examined the evolving role of Artificial Intelligence (AI) in maritime operations, with a particular focus on smart shipping, port automation, and decision support systems (DSS). The findings demonstrate that AI is no longer a peripheral innovation but an increasingly central component in the transformation of the maritime industry toward higher efficiency, safety, sustainability, and operational intelligence. Across the reviewed literature, AI applications such as machine learning, computer vision, predictive analytics, and autonomous systems are consistently shown to enhance decision-making, optimize resource utilization, and reduce human error in complex maritime environments.

In smart shipping, AI-enabled autonomous navigation systems and predictive maintenance tools have significantly improved vessel performance and operational reliability. These technologies contribute to reduced fuel consumption, optimized routing, and enhanced maritime safety through real-time situational awareness and risk prediction. However, the transition toward fully autonomous vessels remains gradual, constrained by regulatory uncertainty, cybersecurity risks, and the need for robust human-machine collaboration frameworks. Despite these limitations, smart shipping continues to represent one of the most transformative areas of AI adoption within the maritime domain.

Port automation has also emerged as a critical area where AI delivers substantial value. Automated container handling systems, intelligent scheduling algorithms, and AI-driven logistics coordination have improved port throughput and reduced congestion in major global hubs. The literature highlights that ports adopting AI-based systems experience increased operational efficiency and improved turnaround times. Nevertheless, disparities in technological infrastructure between developed and developing regions remain a major barrier to uniform adoption, raising concerns about digital inequality within global maritime logistics networks.

Decision support systems powered by AI further enhance maritime operations by enabling real-time data-driven decision-making. These systems integrate data from sensors, satellite systems, and operational databases to support route optimization, weather risk assessment, and emergency response planning. The review indicates that AI-driven DSS significantly improves strategic and tactical decision-making processes, particularly in uncertain and dynamic maritime environments. However, issues related to data quality, interoperability, and trust in algorithmic outputs continue to limit full-scale implementation.

Overall, the study identifies several cross-cutting challenges hindering AI integration in maritime operations, including technological limitations, cybersecurity vulnerabilities, high implementation costs, regulatory gaps, and workforce readiness. Additionally, concerns surrounding ethical AI use, accountability in autonomous decision-making, and data governance remain underexplored but increasingly important.

Looking forward, the future of AI in maritime operations is expected to be shaped by deeper integration with emerging technologies such as the Internet of Things (IoT), blockchain, and 5G-enabled communication systems. These convergences are likely to enhance transparency, traceability, and real-time coordination across global shipping networks. Furthermore, advancements in explainable AI and human-centric automation will be critical in building trust and facilitating wider adoption across stakeholders.

In conclusion, AI presents transformative potential for redefining maritime operations across smart shipping, port automation, and decision support systems. While significant progress has been achieved, the full realization of AI's benefits depends on addressing technical, regulatory, and organizational challenges through coordinated global efforts. Future research should focus on scalable implementation frameworks, standardization of data systems, and inclusive adoption strategies that ensure equitable benefits across the global maritime industry.

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