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Artificial Intelligence and Machine Learning for Green Shipping: Navigating towards Sustainable Maritime Practices

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Abstract— **This paper aims to investigate the role that artificial intelligence (AI) plays in promoting sustainability in the marine industry. The report demonstrates the potential of AI-driven technology to improve vessel operations, decrease emissions, and promote environmental stewardship. This potential is shown by detailed examination of existing trends, problems, and possibilities. Several vital studies highlight the significance of policy interventions that encourage the use of artificial intelligence. These interventions include financial incentives, legal frameworks, and programs to increase capability. Throughout this work, the importance of the role that artificial intelligence plays in driving efficiency, safety, and sustainability is emphasized. This work also highlights the urgent need for action to address climate change and environmental degradation in the marine sector. The marine industry can lessen its carbon footprint, decrease pollution, and improve ecosystem health if it shifts to various alternative fuels, renewable energy sources, and technologies powered by artificial intelligence. At the end of this work, an appeal is made to policymakers, industry stakeholders, and technology providers, urging them to prioritize investments in artificial intelligence research and development and to create collaboration to speed up the transition to a marine sector that is more sustainable and resilient.**

Keywords— **Green shipping; sustainability; renewable energy; artificial intelligence; machine learning.**

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I. INTRODUCTION

Maritime transportation is a crucial player in global transportation [1]; it helps drive the growth of the global economy due to its ability to reduce transportation costs and facilitate speedier intermodal operations across other modes of transportation [2]–[5], which ports serve as crucial links for the transportation of products between the shoreline and the country's interior [6], [7]. In addition, the issue of environmental sustainability has become a significant focus for many marine industries relating to port activities, shipping, and shipbuilding due to the problems posed by climate change and the increasing needs of the logistics and transportation industries [8]–[10]. The augmentation of marine transportation has partially contributed to the growth of urban economies; nevertheless, it has also resulted in resource depletion and environmental damage [11]–[13]. To attain sustainable expansion in urban areas and harbors, employing energy-efficient equipment that minimizes emissions is imperative. Ports are involved with various emissions originating from many sources [14], [15]. The emissions encompass marine vessels, vehicles, and cargo-handling systems, and they significantly impact the ecosystem [16]–[18]. Furthermore, it is crucial to acknowledge that activities such as container drayage and interterminal transit significantly contribute to the emissions generated by ports [19], [20]. Consequently, the need to research environmental improvements at maritime ports, which serve as crucial transportation hubs, has increased. This is because these upgrades enhance several environmental sustainability areas that governments and corporations are striving to address [21], [22].

The marine industry, which plays a significant part in international commerce and transportation, is undergoing significant environmental and technological transformation [23]–[25]. The market places a considerable emphasis on alternative fuels, energy derived from renewable sources, and artificial intelligence (AI), among other essential components. By enhancing sustainability, efficiency, and environmental responsibility, these three pillars have the potential to provide the maritime industry with more significant opportunities for improvement [26], [27]. Traditional fossil fuels, such as oil and diesel, have been depended on by the marine industry for a very long time [28], [29]. These fuels not only contribute to the emission of greenhouse gases but also present the possibility of oil leaks. Alternative fuels, which include liquefied natural gas (LNG), LPG, hydrogen, and biofuels [30]–[34], provide options that are both sustainable and beneficial to the environment [35]–[38]. If the marine sector were to make use of alternative fuels and renewable energy, it would be possible to drastically cut greenhouse gas emissions while simultaneously improving air quality in port regions and coastal zones [39], [40]. Two advantages may be gained by utilizing renewable energy sources such as solar and wind power to generate electricity [41]–[46]. By installing solar panels and wind turbines on ships or harbors, it is possible to reduce the need for fossil fuels while simultaneously providing an environmentally friendly and dependable source of energy consumption [47]–[50]. It is also possible to deploy technologies that generate renewable energy for emission-free powering systems, which is an essential step toward achieving zero-emission shipping [51]–[53].

Artificial Intelligence (AI) has the potential to revolutionize several aspects of many sectors, such as maritime industry, energy, transportation, manufacturing, and agriculture [54]–[63]. In addition, AI has been found to have great potential in other fields such as medicine, society, education, and economy [64]–[68]. With autonomous boats, predictive maintenance, and route optimization, AI may enhance safety, productivity, and decision-making processes [69]–[71]. AI can optimize routes, reduce fuel consumption, and improve operational efficiency by analyzing data gathered from sensors, weather reports, and historical travel records. These three factors must interact for the marine industry to be viable over the long run. For instance, AI can help integrate renewable energy sources and alternative fuels [72]–[74]. Power systems may be efficiently managed by it, ensuring that ships use alternative fuels when available and switch to traditional fuels when needed [75]–[77]. This technique lowers emissions without sacrificing operational stability. Utilizing these technologies also aligns with international efforts to reduce greenhouse gas emissions and address the environmental effects of the marine sector. The International Maritime Organization (IMO) has set aggressive goals to improve energy efficiency and reduce emissions; alternative fuels, AI, and renewable energy will be critical to achieving these objectives. Ultimately, the maritime sector is pivotal in its history, and renewable energy, artificial intelligence, and alternative fuels might significantly influence its future. By adding these elements, the sector may move closer to a more ecologically responsible and sustainable future, reducing its ecological footprint while increasing its efficiency and competitiveness in a constantly changing global market. This research will thoroughly investigate and explain how alternative fuels, renewable energy, and artificial intelligence will disrupt the marine industry. This study aims to understand better the obstacles and possibilities associated with using these cutting-edge technologies and processes. The paper informs policymakers, industry stakeholders, and academics on how these insights might enhance maritime operations' sustainability, efficiency, and environmental stewardship. We wish to contribute to developing well-informed policies and initiatives that will propel the marine industry toward a more environmentally friendly, technologically advanced future.

II. Materials and Method

A. Literature review

The evolution of green marine policies throughout history has been defined by a growing understanding of environmental concerns, the establishment of more sophisticated standards, and a shared determination to limit the ecological effect of the maritime sector. These three factors have been integral to the growth of green marine policies. Concerns about the environmental impact of the shipping sector first surfaced in the later part of the 20th century, when the roots of environmentally aware maritime legislation can be traced back to its beginnings [78]. The increase in pollution, oil spills, and rubbish dumping in seas has been a concern for environmentalists and governments worldwide.

The MARPOL Convention is an international convention created to save the maritime environment and prevent pollution caused by ships. The International Convention for the Prevention of Pollution from Ships (MARPOL), implemented by the International Marine Organization (IMO) in 1973, is considered one of the first and most important international accords that address the issue of pollution in the aquatic environment. Several laws were put into place by MARPOL to limit the pollution produced by ships. These regulations focused on oil pollution, dangerous liquid chemicals, garbage, and air emissions [79], [80]. The futuristic IMPO plan for green shipping is depicted in Fig. 1. On November 2, 1973, the International Maritime Organization (IMO) approved the MARPOL Convention. A string of tanker accidents between 1976 and 1977 led to establishing the Protocol of 1978, which directly responded to those disasters. Because the MARPOL Convention of 1973 had not been implemented, the MARPOL Protocol of 1978 effectively absorbed and superseded the original Convention. The combined document entered into force by the law on October 2, 1983. The Convention was modified in 1997 by the approval of a Protocol, which included the establishment of a new Annex VI [21], [22]. This was one of the amendments that was made. The date when this modification became effective was May 19th, 2005. Throughout its existence, the MARPOL convention has been subjected to alterations in the form of amendments that have been implemented. The Convention includes provisions intended to prevent and decrease pollution produced by ships. These laws include accidental contamination and pollution that result from ships' everyday activities. Currently, there are six technical Annexes inside it. Particular Areas, which are usually included in the majority of Annexes, are responsible for enforcing tight rules on operational discharges [78], [82], [83].

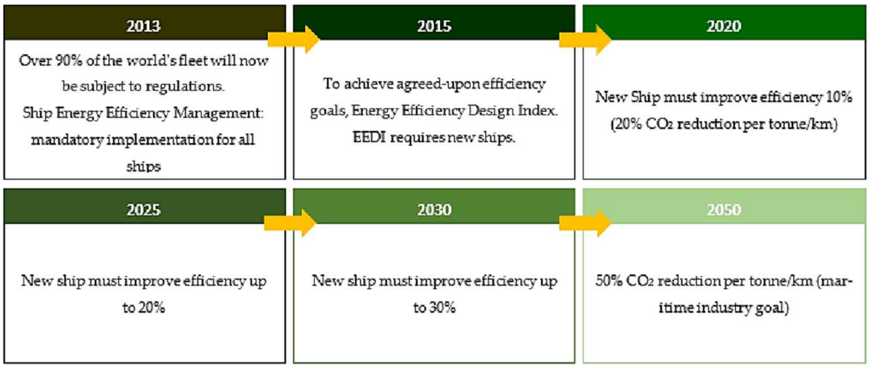


Fig. 1 The IMO plan for green shipping [81]

Throughout its existence, the MARPOL Convention has been subjected to many updates, some of which have been particularly noteworthy, such as Annex VI, which addresses the problem of air pollution created by ships. The implementation of Annex VI in 1997, followed by its strengthening in 2005, resulted in the establishment of stringent rules for the emission of sulfur oxides (SOx) and nitrogen oxides (NOx) from commercial vessels. According to these laws, using fuels with low levels of sulfur and installing catalytic converters are encouraged. Annex VI of the MARPOL Convention was the source of inspiration for the concept of Emission Control Areas, sometimes known as ECAs. More rigorous limits on ship emissions have been implemented in some places, including the Baltic and North Seas. Some laws encourage the deployment of emission-reduction technologies or the use of cleaner fuels. A worldwide sulfur limitation was adopted in 2020 as part of MARPOL Annex VI. This cap is designed to limit the amount of sulfur in marine fuels to 50%. The use of low-sulfur fuels or the deployment of exhaust gas cleaning equipment, also referred to as scrubbers, was encouraged due to this event, which constituted a significant milestone in reducing sulfur dioxide emissions [84]–[86].

The Initial Greenhouse Gas (GHG) Strategy was implemented by the International Maritime Organization (IMO) in 2018. The goal of this plan is to reduce the emissions of greenhouse gases that are caused by global shipping. Compared to the levels recorded in 2008, the level of greenhouse gas emissions from the transportation sector is expected to fall by a minimum of fifty percent by the year 2050. The plan aims to lower the amount of carbon emissions produced for each unit of transportation labor. National and regional bodies have each developed their own ecologically friendly marine regulations in addition to the worldwide standards that have been established [87], [88]. Many of these programs include incentives for using alternative fuels, renewable energy, and technology that are efficient in energy consumption. To ensure compliance with environmental rules, deploying and adopting innovative technology, such as engines that are less harmful to the environment, ballast water management systems, and enhanced waste treatment facilities, have been essential. The historical history of green maritime legislation illustrates the continual development of the marine industry. These regulations are evidence of the industry's commitment to minimizing its environmental impact. As a result of the persistent efforts to implement sustainable practices, the incorporation of alternative fuels, renewable energy, and artificial intelligence, as well as the enforcement of harsher standards, the marine industry has become more environmentally sensitive and efficient [89]–[91]. The policy framework for green shipping and its effects is depicted in Fig. 2.

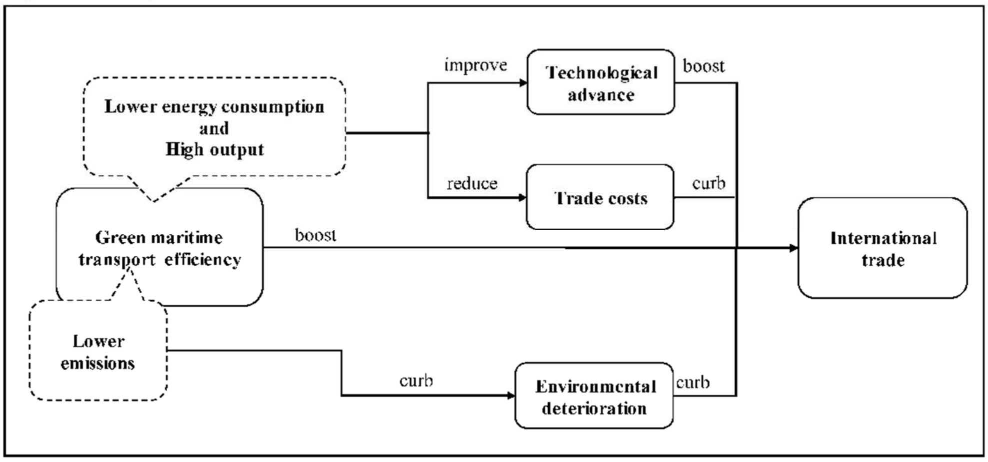


Fig. 2 Policy framework for green shipping and its effects [92]

The International Maritime Organization (IMO), a specialized entity of the United Nations, plays a crucial role in creating and enforcing regulations that apply to the marine sector globally. Many rules apply to environmentally friendly practices in the maritime industry that are enacted by the International Maritime Organization (IMO):

Annex VI of the MARPOL Convention limits the emission of air pollutants from boats. These pollutants include sulfur oxides (SOx), nitrogen oxides (NOx), and greenhouse gases (GHGs) [93], [94]. It is possible to include artificial intelligence in vessel operations to enhance the effectiveness of monitoring and controlling compliance with these standards. The goal of the Energy Efficiency Existing Ship Index (EEXI), which is scheduled to be introduced in 2023, is to improve the energy efficiency of ships that are currently in service [95]–[97]. Ship operators can maximize their boats' performance using artificial intelligence (AI) technologies to meet these objectives.

A framework known as the Carbon Intensity Indicator (CII) was put into place by the IMO as a component of their Initial GHG Strategy. This project aims to create a meter that can measure energy efficiency. Calculating and monitoring the CII of a vessel and identifying possible areas for improvement may be accomplished with artificial intelligence [86]. The different technologies that can be used to improve the green maritime sector are depicted in Fig. 3.

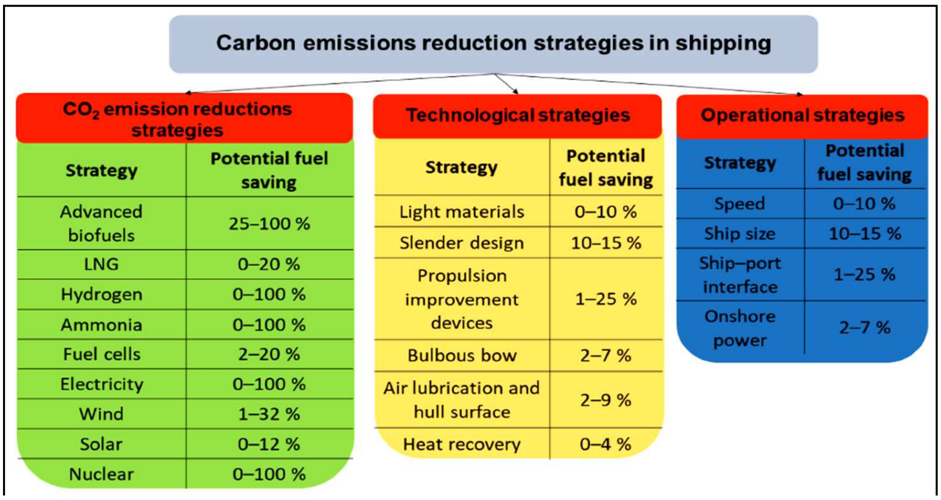


Fig. 3 Various technologies for improvement of the green maritime sector [98]

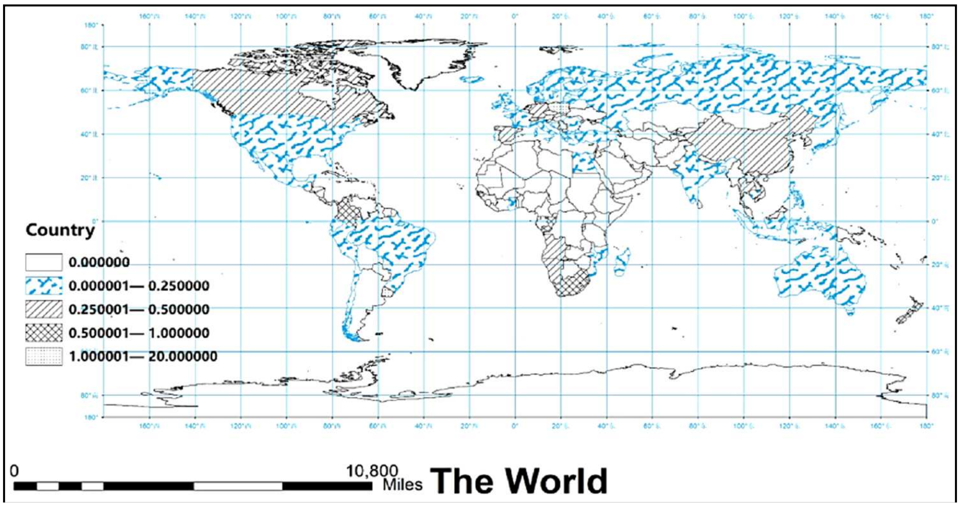


Fig. 4 The geographic distribution of mean green marine transport efficiency per nation [92]

The European Union (EU) has been at the forefront of implementing ecologically friendly maritime rules to cut emissions and advance the cause of sustainability. Among the topics under the purview of EU regulation are those concerning energy efficiency, carbon dioxide emissions, and sulfur emissions [88]. Technologies based on artificial intelligence (AI) have the potential to assist in achieving and exceeding these stringent criteria. The Baltic and North Seas are two examples of areas recognized as Emission Control Areas (ECAs), designated with more rigorous emission regulations. Because ships operating in these locations are expected to comply with higher limitations on emissions, the utilization of technology driven by artificial intelligence to monitor and regulate emissions is becoming increasingly vital [99], [100].

A significant number of countries have enacted their very own laws and regulations concerning emissions, pollution, and environmentally responsible shipping operations. The use of artificial intelligence is highly advantageous since it enables warships to satisfy a wide variety of needs that are constantly evolving. The IMO has recognized the need to address cybersecurity concerns in this age of digitalization. One of the most critical aspects of the digitization of marine operations is using artificial intelligence (AI). It aims to strengthen cybersecurity procedures and protect boats from potential cyber hazards. Due to the growing popularity of autonomous shipping, efforts are being made to build worldwide standards and laws that will ensure the safe and environmentally responsible use of AI-driven autonomous boats. These standards and rules are being developed in response to the growing demand for autonomous shipping [101], [102]. The geographic distribution of mean green marine transport efficiency per nation is depicted in Fig. 4. A flow chart of the ML application process is described in Fig. 5. At the same time, Table 1 is a summary list of recent studies using AI & ML for green shipping.

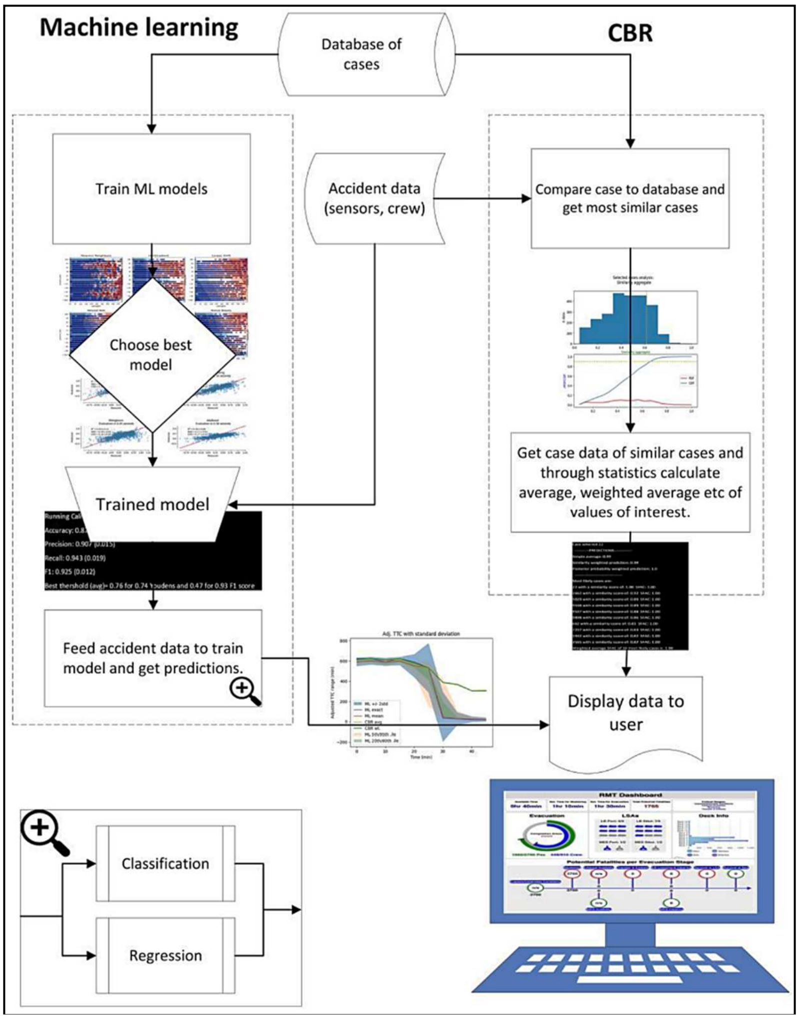


Fig. 5 Flow chart of ML application process [103]

TABLE I
RECENT STUDIES USING AI & ML FOR GREEN SHIPPING

Objectives	ML / AI used	Main outcomes	Source
Model forecasting of sulfur dioxide emission from shipping	Multiple linear regression (MLR), Automated machine learning regressor (AutoML), Gradient descent, and Artificial neural network	The AutoML was superior in data prediction for SO_2 emission.	[17]
Prediction model for onboard photovoltaic system	Extreme learning machines (ELM), kernel density estimation (KDE), and K-mean clustering	ELM could provide at least 5.6% more precise predictions	[104]
Machine learning-based prediction of ship's performance	Principal component regression, Partial least square regression, probabilistic ANN, and ANN	The ML techniques have demonstrated effective performance in simulating ship hydrodynamic conditions, with the probabilistic ANN model being the most effective.	[105]
Prediction optimization of trim in case of container ship	ANN, Decision tree (DT Random Forest (RF), and K-nearest neighbor	The prediction precision of RF was the best, with 88.89% accuracy.	[106]
ML with physics interpretation for ship speed prediction	eXtreme Gradient Boosting (XGBoost) and Physics-informed neural networks (PINNs)	ML may improve speed prediction by 30% when enough data is available for modeling.	[107]
Model-prediction of Manoeuvring emissions	Multiple machine learning techniques	A maneuvering emission impact forecasting model for pilots is constructed with a 73% consistency.	[108]
ML-based prediction of ship's trajectory	Gaussian process regression (GPR)	The proposed ML-based methodology could estimate the probabilistic pattern of grounding risk and ship dynamics.	[109]

Objectives	ML / AI used	Main outcomes	Source
Model prediction of ship performance with tree-based methods	RF, bagging, and boosting	Tree-based modeling offers significant advantages since it delivers excellent accuracy and simplicity of comprehension.	[9]
Hybrid propeller-engine diagram for green shipping	Multiple ML approaches	The groundwork for sophisticated data analytics will be used to determine optimal vessel navigation.	[110]

AI integration within the framework of these policies and regulations involves the utilization of AI for:

- Strategies for monitoring and reducing emissions.
- Implementing predictive maintenance to optimize vessel performance and minimize operational interruptions.
- Optimization of vessel routes to achieve fuel efficiency and minimize emissions.
- Improved safety is achieved by utilizing artificial intelligence-powered autonomous navigation systems.
- The integration of AI in the maritime sector addresses environmental concerns and facilitates compliance with regulations. Furthermore, it offers potential for enhancing the industry's sustainability, efficiency, and safety.
- AI's capacity to foster innovation and promote environmental responsibility in maritime operations is increasingly acknowledged by policymakers and stakeholders.

B. Method

1) Analytical description

Prescribing the main terms and definitions employed during the study is essential. The “Lane” here denotes the entire route of a ship transporting cargo via various ports. The term “Route” represents the distance between two fixed ports. Each route has several alternatives, such as curved or straight. The term “Stretch” means that a route can be broken into many lengths based on the region established by the policy. For example, ECA's policy divides the sea surface into two areas: within the emission control region and outside the control area. There is a path both inside and outside of the emission control area. The route can then be broken into many sections along the boundary of the emission control region. A route can be split into many segments of a defined length. In other words, every section is the same length. To be sure, repeatedly changing speed or heading harms the ship's operation and may increase fuel consumption and emissions. Thus, ships move in a straight line with a constant velocity throughout each segment [111]. In the present study, the ship's sailing speed is initially optimized through the joint application of virtual arrival methods with a carbon tax, emission control area (ECA), and Vessel Speed Reduction Incentive Program (VSRIP). This technique presupposes that the departure and arrival ports are known and that the route has been planned. The speed model's optimization aim is to minimize overall cost. The primary purpose of this section is to determine the objective function.

Fuel expenditures are incurred on all ship journeys. Unit costs vary depending on the kind of fuel. Ships utilize marine gas oil (MGO) throughout ECAs and low sulfur fuel oil (LSFO) outside ECAs for their principal engine fuel. The sulfur content of gasoline used by auxiliary engines is often relatively low, and its unit price is comparable to MGO.c In summary, fuel costs are stated as [111], [112]:

Fuel cost =

$$\sum_{i=1}^{n} \Delta t_1 \{\tau_m P_i^{\,m}[\alpha_i W_L + (1-\alpha_i)W_H] + \tau_a P^a W_L\} \quad (1)$$

Eq. (2) represents the cost that was incurred as a result of the carbon tax measures:

Cost of carbon =

$$W_{CO_2}\left\{\eta CO_2 \sum_{i=1}^{n} \Delta t_i \,(P_i^{\,m} + P^a) - \gamma_{CO_2}.TH_{CO_2}\right\} \quad (2)$$

The amount of time spent sailing determines a portion of the cost. To begin, ships are rented and given a fee proportional to their use time. In the second place, the navigation of vessels requires both labor and equipment as essential components. The costs consist of the salary of the staff members who are on board, the expenses that are essential for living, the fees for maintaining the equipment, the depreciation charge, and the insurance payments. It is calculated with Eq. (3):

$$\text{Cost time} = W_T \sum_{i=1}^{n} \Delta t_i \quad (3)$$

Cost of incentive for speed reduction of the ship needs that the shipping company is entitled to monetary compensation by the VSRIP if the vessel deviates from the designated speed limit within VSRZs in the vicinity of the departure port A and the arrival port B. By diminishing the overall expenses, this component of the cost acquires a negative value. That is articulated as:

Cost owing to VSRIP =

$$-\sum_{port=A,B}^{1} l_{port}\left(v_i \le v_a\right).q_{port}.W_F^{port} \quad (4)$$

While a ship is cruising, fuel oil produces SOx and CO_2. Here's why SOx and CO_2 are used to investigate emission reductions. CO_2 emissions contribute to global warming, while pollutant SOx affect the environment. SOx and CO_2 emissions are the primary targets of emission reduction measures. In this research, ECAs aim to decrease SOx emissions, while carbon pricing schemes aim to reduce CO_2 emissions. Emission levels are determined by the ship's power and gas emission characteristics. This is mentioned in [113]:

$$EM_j = \sum_{i=1}^{n} \Delta t_i \{P_i^{\,m}[\alpha_i n_j^L + (1-\alpha_i) n_j^H] + P^a n_j^L\} \quad (5)$$

In this case, j denotes the type of gas, j = SOx or CO_2. Eq. (5) is used to compute gas emissions once the sailing speed has been calculated to reduce the overall cost under various policies and techniques.

In the above discussion, ‘i' denotes the segmental index, ‘n' represents the total number of segments in a single route, v_a is the threshold of sailing speed, v_i denotes the segmental speed of a ship, v_{max} is the peak speed of the boat, Δt_i is segmental sailing time, T denotes ship's total sailing time on the whole route, ΔT represents the time delay in implementing the

Virtual Arrival strategy. α_i is either 1 or 0 for emission control areas and outside emission control areas, respectively. τ_m denotes fuel consumption for the main engine's fuel consumption in ton/kW·h while τ_a denotes fuel consumption in the case of the auxiliary engine's fuel consumption in ton/kW·h. W_L denotes the cost of marine fuel in dollars per ton, while W_H represents the cost of low-sulfur fuel oil in dollars per ton.

2) Data analysis

The data collected from the ship's logbook through several trips was used as a case study. The data was cleaned and arranged, and descriptive statistical analysis was conducted [114], [115]. The descriptive statistics of the data are listed in Table 2. The descriptive statistical analysis shows that the mean value for Distance is 824.783 nm, the standard deviation is 836.41 nm, and the range of values for Distance is from 0 nm to 6870.7 nm. The average number of hours daily is 78.828 hours, and the standard deviation is 96.61 hours.

TABLE II
DESCRIPTIVE STATISTICAL ANALYSIS

	Distance, nm	**Time, Hr**	**LFO, Gallons**	**DO, Gallons**
count	100	100	100	100
mean	824.783	78.828	66.6992	1.48816
std	836.41	96.61	102.84	4.96
min	0	0	12.955	0.029
25%	461.125	44.9	32.74375	0.09425
50%	653.6	64.05	42.639	0.197
75%	864.925	80.875	59.99075	2.0265
max	6870.7	717	839.884	48.551
Kurtosis	29.22	32.15	34.97	84.23
Skewness	4.67	5.343	5.45	8.84

The range of time is from 0 hours to 717 hours. LFO has a mean of 66.6992 gallons, a standard deviation of 102.84 gallons, and a range from 12.955 gallons to 839.884 gallons. The DO has a mean value of 1.48816 gallons, with a standard deviation of 4.96. The DO may range anywhere from 0.029 gallons to 48.551 gallons. Given that the kurtosis values for Distance, Time, LFO, and DO are 29.22, 32.15, 34.97, and 84.23, respectively, these variables' probability distributions are tail-like. The skewness values for Distance, Time, LFO, and DO are 4.67, 5.343, 5.45, and 8.84, respectively, illustrating the level of asymmetry around their respective means. The presence of a positive skew indicates a longer right tail, while the presence of a negative skew indicates a longer left tail. Higher absolute values indicate a higher deviation from the mean.

3) Machine learning for model-prediction:

Extreme Gradient Boosting, or XGBoost, is a robust and frequently used machine learning method well-known for its effectiveness and simplicity in managing structured and tabular data. It is a member of the family of methods known as ensemble learning, and it works by iteratively constructing an ensemble of weak learners, often decision trees, to generate a robust predictive model. Using regularization to minimize overfitting and the minimization of a particular loss function, XGBoost can perform very well in regression and classification exercises. Gradient boosting, which successively corrects mistakes caused by earlier models, and approximation tree learning, which accelerates training by creating trees level-wise, are two of its main properties. Both of these elements are among its most essential characteristics. The success of XGBoost may be attributed to its capacity to generate very accurate predictions and its adaptability in various areas [116], [117]. As a result, it is quickly becoming the tool preferred by data scientists and machine learning practitioners. The following is the procedure followed:

If the training data set is defined as:

$$D = \{(x_i, y_i)\}_{i=1}^{n} \tag{6}$$

In this case, the is feature vector while y_i denotes the corresponding label for i_{th} sample.

The objective of XGBoost is to learn the additive ensemble of weak learners

$F(x) = \sum_{k=1}^{K} f_k(x)$; herein, each denotes a regression tree.

The objective function of XGBoost is given as:

$$Obj = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{7}$$

Herein, $L(y_i, \hat{y}_i)$ the loss function is the actual value while denoting the predicted value. The model is trained repeatedly by introducing weak learners into the ensemble. In each cycle, a new regression tree is trained with the aim of minimizing the following objective function:

$$Obj_k = \sum_{i=1}^{n} L(y_i, \hat{y}_i^{\,t}) + \sum_{i=1}^{t} \Omega(f_i) + \gamma.T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \tag{8}$$

In this expression, T denotes the number of leaves and λ represents the regularization term defining the complexity of the tree. Following training, the final prediction for a fresh sample x is derived by adding the forecasts of all regression trees in the ensemble: herein, the forecast of the k_{th} tree.

III. RESULTS AND DISCUSSION

A. Results

1) Preprocessing

Data preparation, which includes developing correlation heatmaps, ensures analytical integrity, trustworthiness, and efficacy. These processes are critical to research and analysis for the following reasons. Correlation heatmaps demonstrate the correlations between dataset variables. They let researchers determine how variables interact, whether they are positively or negatively related, and how much. This information is essential for choosing model predictors and identifying multicollinearity concerns. Identifying strong connections might help you choose features by reducing duplicate data points irrelevant to the investigation**.** Fig. 6 displays the correlation heatmap for the research data. The data is about green shipping using a mix of low-sulfur oil (LSO) and diesel oil (DO).

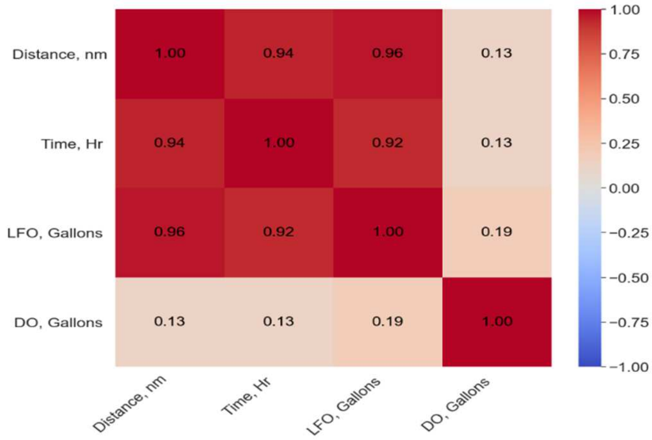
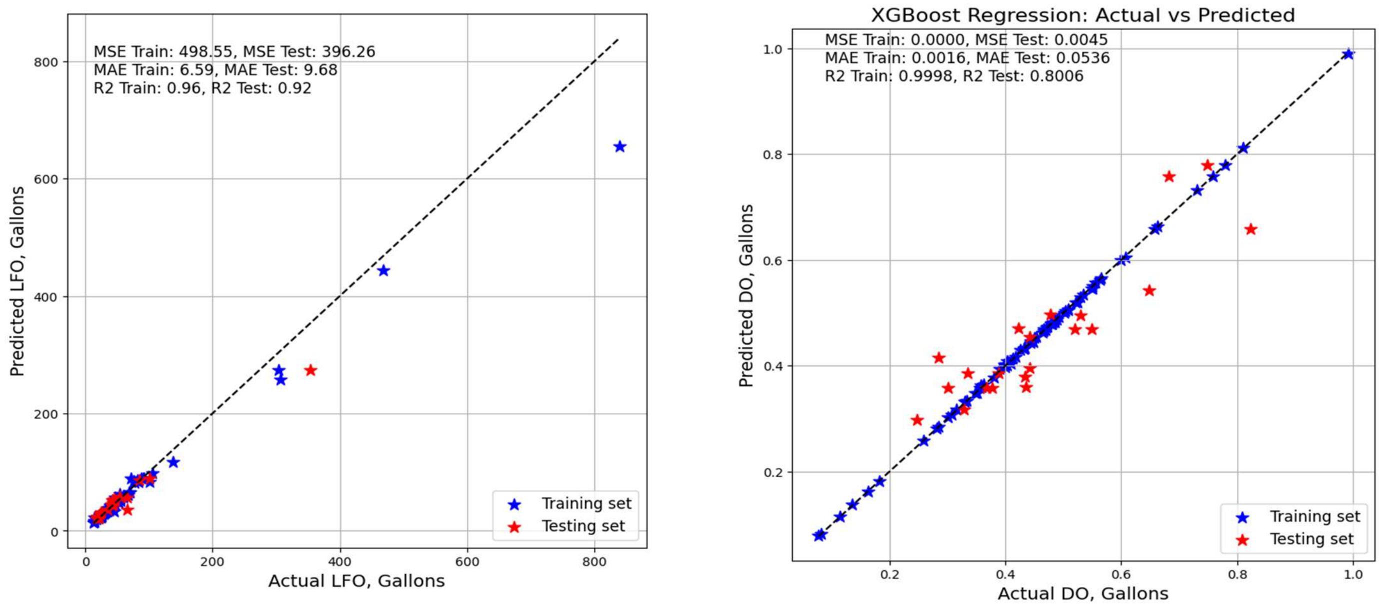


Fig. 6 Correlational heatmap

2) Model-prediction



(a) (b)

Fig. 7 XGBoost-based model's actual vs predicted (a) LFO data (b) DO data

The results of the experiments that were carried out to demonstrate the prediction capabilities of the machine learning model XGBoost on ship fuel consumption data are shown in this part of the findings. In this section, the model development process is broken down in great depth, and a comprehensive analysis of the advantages and disadvantages of each model is presented. The prediction model was developed using a systematic process comprising data preparation, feature engineering, model selection, hyperparameter tuning, and rigorous evaluation. This method was followed for every one of the models. Ship-related data, such as the distance traveled by the vessel, the time it took, and the amount of fuel used in the past, was gathered and analyzed for training purposes. To consider the time dependency, the feature engineering process included the development of lag features and the data standardization to achieve consistent scaling, as shown in Fig. 7.

R-squared, Mean Squared Error (MSE), and Mean Absolute Error (MAE) are three metrics that may describe the LSO and DO models based on XGBoost. These metrics can be utilized for both the training and test datasets. Beginning with the LSO model, it was observed that the R-squared values are high in both the training dataset and the test dataset. This indicates a significant connection between the predicted values of the fuel-related variable and the actual values of the variable. The value of R squared in the training dataset is 0.96, which indicates that the model can explain about 96% of the variation in the variable that is associated with fuel. Similarly, the R-squared score in the test dataset is slightly lower at 0.92, which indicates that the model continues to perform well on data it has not seen before. There are quite a few mistakes between the predicted values and those observed, as shown by the MSE values for LSO, which are 498.55 for the training dataset and 396.26 for the test dataset. The MAE values for the training dataset are 6.59, whereas the MAE values for the test dataset are 9.68. This further substantiates the model's accuracy in predicting fuel-related variables when using low-sulfur fuel oil.

Moving on to the DO model, their R-squared values were even higher than those of LSO. This is especially true in the training dataset, where it reaches 0.9998, which indicates that there is a robust correlation between the values that were predicted and the values that were observed. The R-squared value, on the other hand, lowers to 0.8006 in the test dataset, which indicates that the model's performance on data that has not yet been seen has somewhat decreased but has still retained a pretty high degree of correlation. Within the training dataset, the MSE values for DO are very near zero, indicating very few mistakes between the predicted and actual values. Furthermore, the MSE value in the test dataset is 0.0045, which is also considered extremely low. While the MAE values in the training dataset are near zero (0.0016), they are reasonably tiny in the test dataset (0.0536), demonstrating that the model accurately predicts fuel-related variables when diesel oil or distillate fuel oil is used. When employed as predictors for the fuel-related variable, both kinds of ship fuels, LSO and DO, have solid correlations and low prediction errors. The high R-squared values and the low

MSE and MAE values across the training and test datasets demonstrate this.

B. *Policy suggestions*

1) *Environmental implications*

The marine sector may see significant environmental implications, good and bad, due to adopting technology such as artificial intelligence (AI), renewable energy sources, and alternative fuels. An analysis of these effects is presented as follows:

GHG reduction: One of the most important advantages of implementing alternative fuels and renewable energy sources in the marine sector is the massive decrease in greenhouse gas emissions. This is one of the critical benefits of this adoption. Traditional marine fuels, such as heavy fuel oil, are responsible for the emission of significant quantities of certain pollutants, including carbon dioxide (CO_2), sulfur oxides (SOx), and nitrogen oxides (NOx) [118], [119]. The adoption of more environmentally friendly alternatives, such as liquefied natural gas (LNG), hydrogen, or biofuels, has the potential to reduce these emissions significantly, therefore contributing to the mitigation of climate change and the improvement of air quality [120], [121].

Marine pollution mitigation: Traditional marine fuels contribute to air pollution and carry concerns of oil spills and water contamination. Air pollution is a significant contributor to marine pollution. Alternative fuels, such as LNG, offer a decreased risk of leaks and can contribute to reducing pollution in maritime environments. A further reduction in dependency on fossil fuels and the danger of oil spills can be achieved by using renewable energy sources such as wind and solar power to provide auxiliary power [122], [123].

Energy efficiency enhancement: Artificial intelligence technology may be utilized to optimize vessel operations, resulting in enhanced energy efficiency and decreased fuel usage and consumption. Intelligent systems powered by artificial intelligence can optimize ship routes, modify speeds based on weather conditions, and operate onboard systems more effectively, ultimately resulting in substantial fuel savings and emissions reductions [124], [125].

Impact on marine ecosystem: Despite the potential of alternative fuels and renewable energy sources to lessen the amount of pollution caused by maritime activities, implementing these technologies may have an indirect effect on marine ecosystems. The manufacturing and distributing biofuels and installing offshore wind farms are two examples of activities that can potentially damage aquatic ecosystems and habitats. Careful planning and extensive environmental impact studies are required to minimize these consequences and ensure the deployment of these technologies in a sustainable manner [126], [127].

Consumption of resources: The creation and deployment of artificial intelligence technology, alternative fuels, and infrastructure for renewable energy all demand significant resources, such as land, water, and materials. Depending on how these resources are obtained and maintained, environmental implications may be connected with them. These impacts may include the loss of habitats, the use of water, and increased carbon emissions related to manufacturing operations. To lessen the severity of these effects, it is necessary to encourage sustainable methods in the extraction, production, and disposal of resources and waste [87], [91].

Long-term sustainability: In the framework of long-term sustainability, it is necessary to take into consideration the environmental advantages that would result from the marine industry's use of alternative fuels, various forms of renewable energy, and artificial intelligence. The widespread adoption of these technologies should align with broader sustainability goals, such as preserving biodiversity, protecting ecosystems, and equitable distribution of environmental benefits and burdens. Although these technologies present opportunities to reduce environmental harm in the short term, their widespread adoption should align with these broader sustainability goals [128], [129].

Using alternative fuels, renewable energy sources, and artificial intelligence technologies in the maritime sector can drastically cut greenhouse gas emissions, lessen marine pollution, and increase energy efficiency. However, to guarantee that these technologies effectively contribute to achieving long-term sustainability objectives, seriously considering the potential environmental repercussions is necessary.

2) *Economic implications*

Cost Savings: Artificial intelligence technologies can potentially optimize various nautical activities, resulting in business cost savings. As an illustration, predictive maintenance systems powered by artificial intelligence can assist in predicting the breakdown of equipment, enabling prompt repairs and reducing downtime. Similarly, AI-driven route optimization algorithms can minimize the amount of fuel consumed and the duration of voyages, resulting in cheaper operational costs for shipping corporations [82], [130].

Efficiency enhancements: Artificial intelligence can improve operational efficiency throughout the marine supply chain. AI technologies can potentially enhance overall efficiency and resource utilization, which may result in cost savings for enterprises. This can be accomplished by automating repetitive jobs, optimizing logistics and inventory management, and expediting cargo handling procedures [131], [132].

Market opportunities: The implementation of artificial intelligence in the marine sector has the potential to provide new income streams and market opportunities. There is a possibility that businesses that utilize artificial intelligence for predictive analytics, autonomous navigation, or intelligent port management may gain a competitive advantage and attract new consumers who are looking for creative and efficient marine solutions [133], [134].

Reduction of risk: Risk management systems driven by artificial intelligence can analyze vast volumes of data to detect possible safety hazards, security threats, and operational risks. Marine firms can reduce disruptions, avoid costly accidents, and preserve regulatory compliance by taking proactive measures to handle these risks. This will reduce financial obligations and insurance premiums [135], [136].

3) *Society impacts*

Job creation: Artificial intelligence has the potential to generate new employment possibilities, even though there are worries over the displacement of people in the marine sector by automation. There will be an increase in the need for skilled individuals in industries such as data science, software development, robotics, and AI system maintenance due to the increasing number of organizations investing in artificial intelligence technology. Additionally, breakthroughs that are driven by artificial intelligence have the potential to encourage employment development in similar areas, such as engineering, technology, and logistics [137], [138].

Better health results: Artificial intelligence applications in the marine industry have the potential to improve crew safety and well-being, which in turn can contribute to better health results. For instance, through predictive analytics driven by artificial intelligence, it is possible to identify potential health problems among crew members, enabling preemptive interventions and preventative actions. Additionally, autonomous and remotely operated vessels equipped with collision avoidance systems based on artificial intelligence can potentially lower the likelihood of accidents occurring at sea, therefore protecting the lives and health of maritime personnel [137], [139].

Environmental benefits: When it comes to marine operations, using artificial intelligence may result in significant environmental benefits that, in turn, improve social well-being. Although these benefits are not directly tied to economic gains, they are still important. Innovations in the maritime industry driven by artificial intelligence assist in preserving ecosystems, maintaining natural resources, and protecting the health of populations that rely on marine ecosystems for their sustenance and happiness. These innovations help reduce greenhouse gas emissions, mitigate marine pollution, and promote sustainable practices [78], [140].

In conclusion, AI provides various economic benefits, such as cost reductions, increases in efficiency, and possibilities in the market. Additionally, it delivers social benefits, such as creating jobs and improved health outcomes for marine workers and communities. To ensure that the implementation of artificial intelligence in the marine sector has the greatest possible good influence on society, addressing potential issues such as the displacement of workforces and ethical considerations is vital.

4) Challenges and barriers

Putting into practice environmentally friendly policies and artificial intelligence solutions in the marine sector is met with several hurdles and impediments, which may be broken down into four categories: technological, regulatory, economic, and cultural. A summary in this regard is depicted in Fig. 8.

Technological obstacles:

- The process of retrofitting older vessels with environmentally friendly technologies or adopting artificial intelligence solutions can be technically demanding and expensive simultaneously. Because of this, it could be necessary to make considerable adjustments to the infrastructure and systems on board.
- The importance of ensuring the dependability and safety of artificial intelligence (AI) systems and environmentally friendly technology in marine operations cannot be overstated. Accidents or disruptions in operations might be caused by technical faults or malfunctions, which would pose a threat to the safety of the crew as well as the environmental sustainability of the environment.
- Artificial intelligence systems depend on having access to vast amounts of high-quality data to train and make decisions. Interoperability problems and data silos within the marine sector, on the other hand, might be obstacles to the successful adoption of AI-driven solutions

Regulatory obstacles:

- Maritime stakeholders must comply with green policies and regulations to reduce emissions and promote sustainable practices. These policies and laws place compliance duties on maritime stakeholders. Implementing these requirements may require substantial financial investments in technological improvements and operational modifications.

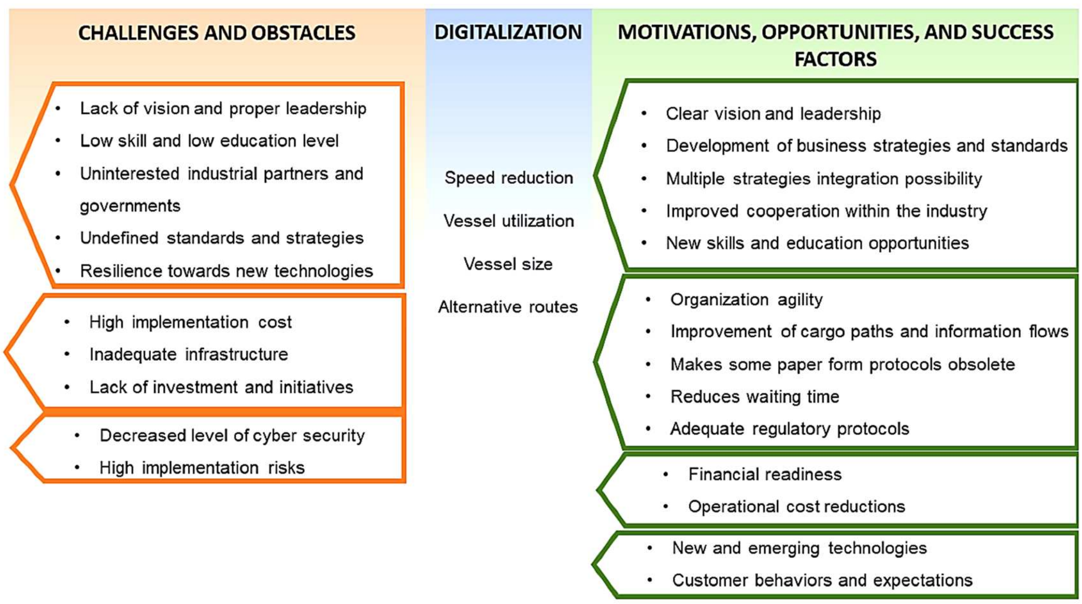


Fig. 8 Summary of challenges and opportunities [98]

- Regulation uncertainty: The rapid growth of artificial intelligence and environmentally friendly technology presents regulatory organizations with difficulty in defining clear and consistent standards. Regulatory ambiguity can create obstacles that prevent innovation and investment in environmentally friendly solutions.
- International Coordination Due to the maritime industry's global nature, multiple stakeholders, such as governments, international organizations, and industry associations, must coordinate efforts to harmonize regulatory frameworks and guarantee that environmental and safety standards are consistently enforced.

Economic challenges:

- The implementation of green policies and artificial intelligence solutions sometimes necessitates considerable initial investments. This may discourage specific marine organizations, tiny and medium-sized enterprises (SMEs), from embracing these technologies.
- Evaluating the long-term economic advantages of green technologies and artificial intelligence solutions can be difficult owing to the uncertainties surrounding fuel pricing, improvements in regulatory policies, and technological breakthroughs. Without clear proof of return on investment, businesses could hesitate to invest.
- It may be difficult to obtain finance for artificial intelligence and green projects, particularly for small and medium-sized enterprises (SMEs) and businesses that operate in emerging countries. To encourage the widespread adoption of environmentally friendly and technology-driven solutions in the marine industry, it is vital to address the limits that may be imposed by funding.

Organizational and cultural structure:

- The adoption of green policies and artificial intelligence solutions can be hampered by resistance to change, which can be considered cultural opposition inside marine companies and conventional views toward innovation and sustainability. To successfully overcome opposition to change, leadership must demonstrate commitment, employees must be trained, and stakeholders must be engaged.
- Data analytics, machine learning, and cybersecurity are all areas in which specialist expertise is required to implement artificial intelligence solutions in the marine business successfully. To guarantee the effective deployment and exploitation of artificial intelligence technologies, it is vital to address the skills gap by implementing education and training programs.
- Collaboration across stakeholders: Effective collaboration across a wide range of stakeholders is required to successfully implement green policies and artificial intelligence solutions. These stakeholders include shipowners, operators, regulators, technology suppliers, and research institutes. Establishing trust and cultivating relationships among various stakeholders is paramount to overcome obstacles and propel collective action toward sustainability and innovation.

In conclusion, to overcome the issues and hurdles that the maritime sector is encountering when attempting to implement green policies and AI solutions, it is necessary to take a multidimensional strategy that includes technology innovation, legislative reform, economic incentives, and cultural transformation. It is vital to collaborate among stakeholders and take proactive actions to overcome technical, regulatory, financial, and organizational constraints to achieve the full potential of technology-driven solutions that are sustainable and environmentally friendly in the marine industry.

5) Policy recommendations for promoting green maritime practices and integrating AI solutions

Establish clear regulatory frameworks:

- To encourage the marine sector to use environmentally friendly technology and artificial intelligence solutions, regulatory frameworks that are both comprehensive and uniform should be developed.
- To drive decarbonization activities effectively, it is necessary to establish emission reduction objectives and put environmental solid regulations in place, such as imposing limits on sulfur and nitrogen oxide emissions.
- Legislative incentives should be provided to stimulate investment in environmentally friendly technology and AI-driven efficiency gains. These incentives might be tax breaks, subsidies, or carbon trading programs.

Investment in research and development:

- Funding should be allocated for research and development projects that aim to enhance artificial intelligence solutions and environmentally friendly technology for the marine industry.
- To speed up innovation in alternative fuels, autonomous shipping, and predictive maintenance, it is essential to encourage collaboration between industry players, academic institutions, and research groups.

Collaborative learning and development of capabilities:

- to enhance the skills and capacities of marine professionals in artificial intelligence, data analytics, and sustainability, it is necessary to establish training programs and platforms for knowledge sharing.
- Make sure that there is a steady supply of qualified individuals for the marine sector by providing financial assistance to workforce development projects and educational institutions that offer courses in disciplines relevant to the industry.

Encourage public-private partnerships:

- The development and implementation of environmentally friendly marine solutions should be facilitated by public-private partnerships (PPPs), which should encourage collaboration between governments, industry participants, and technology suppliers.
- To encourage the adoption of AI-driven technologies and best practices, it is necessary to establish platforms for sharing information and cooperation. Some examples of such platforms should include industry consortia, innovation centers, and demonstration projects.

Facilitate the exchange of Information and interoperability:

- Establishing standards and procedures for collecting, storing, and exchanging data is a great way to encourage data sharing and interoperability across several stakeholders in the marine industry.
- Create frameworks that will allow for the exchange of anonymized data for the sake of research while at the same time preserving sensitive business information and maintaining the privacy and security of data.

Financial incentives and support mechanisms:

- The use of environmentally friendly technology and artificial intelligence solutions by marine firms should be supported by providing financial incentives such as grants, loans with low interest rates, and investment tax credits.
- To finance sustainability initiatives and technological improvements in the marine industry, green financing methods should be established. Some examples of such mechanisms are green bonds and revolving funds.

Promote international collaboration and knowledge exchange:

- Multilateral forums, such as the International Maritime Organization (IMO) and regional maritime organizations, should be utilized to facilitate international collaboration and the exchange of information.
- To promote the worldwide shift towards environmentally responsible and technology-driven marine activities, sharing best practices, lessons learned, and newly developed technical advances is essential. In addition, it should enhance students' and learners' awareness of the importance of protecting the environment [141].

Monitoring and evaluating progress:

- Establish systems for monitoring and assessing the application of green marine policies and artificial intelligence solutions. These mechanisms should include the tracking of emission reductions, improvements in energy efficiency, and the deployment of technology [142].
- To ensure that regulatory frameworks and policy measures are successful, identifying areas in which they may be improved, and adapting to changing technical and market trends, it is essential to conduct periodic reviews.

Implementing these policy proposals will enable policymakers to create an atmosphere favorable to including artificial intelligence solutions and promoting environmentally friendly maritime practices. This environment will be conducive to the development of ecologically friendly maritime practices. As a consequence of this, the marine sector will be able to experience sustainable expansion and innovation while also addressing concerns regarding the environment.

6) Need for *incentives, subsidies, and regulatory frameworks that consider AI*

To speed the adoption of technology-driven solutions and environmentally responsible practices, it is vital to incorporate regulatory frameworks, incentives, and subsidies that consider artificial intelligence in the marine industry. To facilitate the incorporation of AI, these steps can be adapted in the following manner:

Financial incentives for the implementation of AI:

- Provide marine enterprises investing in artificial intelligence technology with financial incentives, such as grants, subsidies, or tax credits, that are expressly targeted toward them.
- It would be beneficial to provide money for pilot projects and demonstrations demonstrating artificial intelligence's advantages in boosting efficiency, safety, and environmental performance within the marine industry.
- Establish incentives that are based on performance and are related to outcomes that are driven by artificial intelligence, such as increases in fuel economy, reductions in emissions, or savings in operating costs.

Support for research and development via subsidies:

- Allocate subsidies and research grants to assist research and development efforts focused on creating artificial intelligence solutions suited to the marine sector's specific difficulties and requirements.
- Encourage collaboration between public research organizations, universities, and entities from the business sector through research partnerships that are financially supported to enhance artificial intelligence applications in marine operations.

Frameworks for the regulation of Artificial Intelligence:

- To address the ethical, safety, and liability problems that are linked with the use of artificial intelligence in marine operations, regulatory frameworks should be developed.
- To guarantee that artificial intelligence technologies are used responsibly within the maritime sector, it is necessary to establish principles for AI governance. These guidelines should include algorithm transparency, data privacy, cybersecurity, and accountability criteria.
- To facilitate the worldwide adoption of AI-driven solutions in marine shipping, it is essential to collaborate with international organizations and industry players to unify artificial intelligence rules across different jurisdictions.

Developing capabilities and providing training programs:

- Training programs and capacity-building projects centered on developing artificial intelligence capabilities should be made available to marine professionals such as ship operators, engineers, and data analysts [143], [144].
- For marine enterprises engaging in staff training and upskilling programs connected to artificial intelligence technology and data analytics, provide financial help through subsidies or tuition aid.
- Work with educational institutions and training providers to produce customized training programs and certification courses specifically designed to meet the artificial intelligence requirements of the marine sector [145], [146]. In addition,

Innovation in Artificial Intelligence through public-private partnerships:

- To co-fund artificial intelligence (AI) innovation initiatives and technology pilots that solve critical difficulties in marine transportation, such as autonomous navigation, predictive maintenance, and emissions monitoring, it is highly recommended that public-private partnerships (PPPs) be facilitated.

- To make the most of the aggregate experience and resources available, it is essential to encourage collaboration between government agencies, industry groups, technology suppliers, and academic institutions to create artificial intelligence solutions for the marine industry toward the goals of era 4.0 and 5.0 for transportation sector [147], [148].

To prototype and verify novel artificial intelligence applications in real-world marine contexts, it is essential to establish innovation clusters or testbeds where maritime enterprises may work with artificial intelligence startups and researchers. To encourage investment, innovation, and collaboration within the maritime industry, policymakers can incorporate incentives, subsidies, and regulatory frameworks specifically designed to consider artificial intelligence [149], [150]. This will ultimately lead to adopting AI-driven solutions that improve maritime operations' sustainability, efficiency, and safety.

IV. Conclusion

In conclusion, our investigation sheds light on the significant part that artificial intelligence plays in facilitating the shift to environmentally responsible practices in the marine industry, in conjunction with using alternative fuels and renewable energy sources.

- AI facilitates a shift to environmentally responsible practices in the marine industry.
- Utilizing predictive maintenance systems, route optimization algorithms, and autonomous shipping capabilities.
- Enhancing decision-making processes and vessel operations and reducing pollutants and fuel consumption.
- Recommendations for public policy include financial incentives, legal frameworks, and capacity-building activities.
- Urgent need for action to address climate change and environmental deterioration in the marine industry.
- Shifting to alternate fuels, renewable energy, and AI to reduce environmental impact and pollution.
- Future success requires a holistic strategy incorporating AI, alternative fuels, and renewable energy.
- Policymakers should prioritize AI research, encourage stakeholder cooperation, and create regulatory settings conducive to collaboration.

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