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Review: The necessity of implementing AI for enhancing safety in the Indonesian passenger shipping fleet

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Abstract

The shipping industry, grappling with escalating challenges, increasingly adopts Artificial Intelligence (AI) to enhance efficiency, safety, and environmental impact. Experts endorse ship automation and AI implementation for safety, navigation, and operational efficiency in ferry networks. This paper underscores AIS technology's role in maritime safety and environmental protection, emphasizing AI's potential in navigation and knowledge gap bridging. Indonesia, with its numerous islands and significant population, faces complex challenges in ensuring safe maritime transportation. Collaborative efforts among the government, industry, and stakeholders are vital for enhancing safety standards across the archipelago. Despite regulations, Indonesia contends with a high ferry accident rate, prompting the need for preventive measures. The study reviews AI's application in preventing sea accidents, recognizing its contributions and potential effectiveness in maritime safety. Acknowledging challenges like data quality and cybersecurity, the paper emphasizes the necessity of AI development for passenger ship safety. It concludes by highlighting significant research efforts, endorsing AI's promising role in reshaping the industry for improved efficiency and safety. Further exploration of AI applications, particularly in passenger ship safety, is recommended to meet evolving challenges in the maritime sector.

1. Introduction

The shipping industry grapples with rising challenges, addressing them with AI for efficiency, safety, and environmental impact. Ehlers et al. [1] highlights the recommendation of experts in the maritime domain to automate ships and implement AI for improved safety and navigation. Yuen et al. [2] discusses the use of AI to achieve operational efficiency in shipping, such as optimizing ferry networks and predicting ship energy performance. The role of Automatic Identification System (AIS) technology in improving maritime safety and environmental protection [3]. The potential of AI in maritime navigation, highlighting the challenges and gaps in knowledge and technology [4]. Overall, these papers demonstrate the industry's recognition of AI as a valuable tool for addressing the challenges it faces.

Indonesia is a country with numerous islands and a large population, making the provision of safe ships a significant challenge. With the need for efficient and safe maritime transportation, joint efforts are required to enhance safety standards across this archipelagic region. This challenge involves coordination among the government, industry players, and other stakeholders to ensure that every sea journey in Indonesia takes place safely and effectively, maintaining connectivity between islands and supporting economic development and the lives of people throughout the country. Liu et al. [5] emphasizes the need for safer and more efficient vessel designs in Indonesia's coastal transport and fishing operations. Romadhon and Vikaliana [6]. discusses the importance of people's voyages and the need for alternative solutions to address the procurement of shipping fleets and ensure safety and service quality. The significance of people's voyages and the government's commitment to improving safety and security while considering local wisdom. Faturachman and Shariman [7] focuses on ship safety assessment strategies in Indonesia, considering factors such as software, hardware, environment, and live-ware.

Indonesian law regulates shipping safety and security; however, the ferry accident rate is high. According to Law of the Republic of Indonesia Number 17 of 2008, Chapter VIII, Article 116, Paragraph 1, shipping safety and security encompass transportation safety in water areas, port zones, and the protection of the marine environment. The Government executes shipping safety and security in its implementation, considering water transportation safety and security as imperative for meeting ships' seaworthiness and navigation requirements [8] [9]. Indonesia's geographical location, spanning Asia and Australia and situated between the Indian and Pacific Oceans, designates its maritime territory as a crucial international shipping lane [10]. With over 17,000 islands extending from Sabang to Merauke, Indonesia ranks as the world's largest archipelagic country. Maintaining connectivity among these islands requires a robust sea transportation system. Unfortunately, based on data from the BMPV accident database, as published in "Safety of Domestic Ferries: A Scoping Study of Seven High Risks," Indonesia registers a high death rate in the ferry transportation sector, reaching 4,758 people between 2000 and 2021 [11], see Figure 1 and Figure 2.

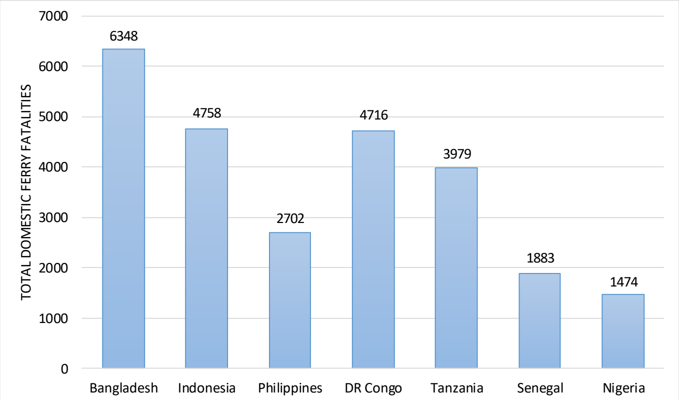

Figure 1. Total domestic ferry fatalities in Indonesia between 2000-2021 [11]

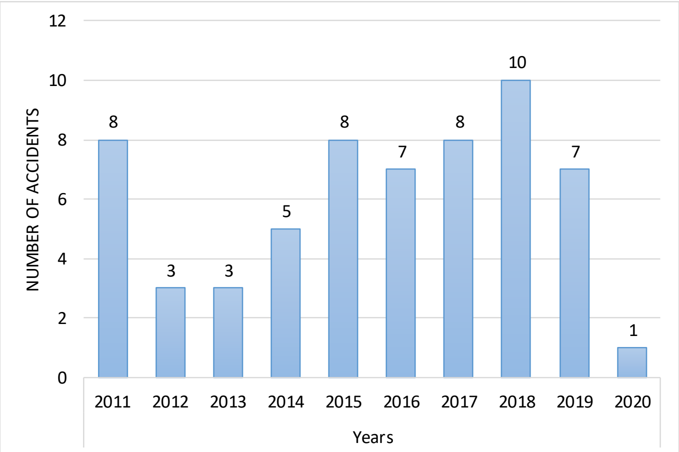

Figure 2. Trend of accidents in Indonesia Safety of domestic ferries in Indonesia [11]

The development of artificial intelligence technology is considered capable of addressing various issues, including in the maritime field. Kontzinos et al. [12] highlights the implementation of AI approaches in the maritime industry to effectively process and analyze large amounts of data for safety, performance, energy efficiency, automation, and environmental impact. Yu and Cheng [13] discusses the application of AI in ocean development, including intelligent navigation, unmanned probes, and the use of digital ocean platforms. Dillingham and Perakis [14] focuses on the application of AI and expert systems in marine operations, such as optimal container stowage and ship monitoring. Overall, these papers demonstrate the increasing importance and expanding applications of AI in the maritime industry.

With the high incidence of accidents, there is a need for preventive efforts through specific measures, where the implementation of artificial intelligence (AI) is considered to address this challenge. This article aims to evaluate the achievements of AI application in preventing sea accidents. Through this review, it is hoped that the extent of AI's contribution to enhancing maritime safety and reducing detrimental incidents can be identified. The conclusion of this research is expected to provide a clear insight into the potential and effectiveness of using AI technology in achieving the goals of maritime accident prevention.

2. Increased Safety with the AI application

The improvement of ship safety in Indonesia takes center stage through the implementation of artificial intelligence (AI). The safety conditions of ships are assessed by considering related factors in ship accidents. AI technology assists in identifying risks in the shipping community and supports intelligent ship navigation. Artificial intelligence is also applied in designing ship safety and optimizing activities in ports. Thus, the integration of AI in various aspects of maritime operations is expected to enhance safety and operational efficiency.

2.1 Ship Safety Conditions in Indonesia

Despite a slight decline, Indonesia continues to experience a high number of accidents, particularly with an annual increase in incidents involving passenger ships. According to a literature database, over the course of a decade, spanning from January 1, 2011, to January 1, 2021, there were a total of sixty incidents involving domestic passenger vessels in Indonesia [11]. It is noteworthy; however, the data indicates a modest downward trajectory in the frequency of accidents and annual fatalities recorded throughout the preceding decade. (as illustrated in Figure 1 and Figure 2). Careful interpretation of this trend is essential, particularly given that Indonesia reported the highest number of accidents among the seven countries that were studied [11].

According to data from the Indonesian National Transportation Safety Committee (KNKT), there were 142 incidents involving vessels in Indonesia or vessels with Indonesian flag between 2017 and 2022, with the proportion of accidents related to passenger ships progressively rising each year. (as depicted in Figure 3) [15], [16]. Out of the 142 ship accidents in Indonesia, KNKT reported 742 victims, comprising 636 fatalities and 106 injuries (as detailed in Table 1) [15], [16].

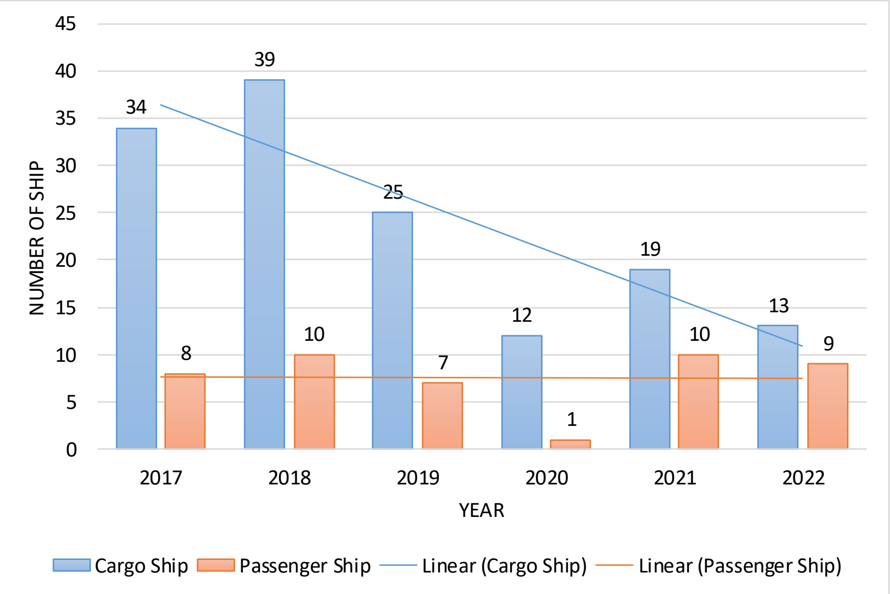

Figure 3. Comparison of the number of accidents of cargo and passenger ships in Indonesia between 2017-2022 [15] [16]

Table 1. Accident' s victim in Indonesia between 2017-2022 [15] [16]

No.	Ship Accident' s Victim	Year						Total
		2017	201	2019	2020	2021	2022	
1	Death	52	299	92	11	96	86	636
2	Injured	3	26	10	33	27	7	106
	Total	55	325	102	44	123	93	742

These alarming statistics underscore the critical need for enhanced safety measures within Indonesia's maritime sector. The consistent rise in annual accidents involving passenger ships is a cause for concern, warranting a comprehensive examination of the underlying factors contributing to these incidents. Efforts to reverse the upward trajectory of passenger ship accidents should involve a multi-faceted approach, including rigorous safety regulations, advanced technological interventions, and targeted awareness campaigns. The data provided by the Indonesian National Transportation Safety Committee (KNKT) serves as a crucial foundation for formulating evidence-based strategies to mitigate risks and improve the overall safety of maritime activities in the region. Additionally, collaborative initiatives involving relevant stakeholders, such as government agencies, shipping companies, and safety organizations, are essential to effectively address and rectify the identified challenges in order to ensure a safer maritime environment for all.

2.2 The related factors in ship accidents

Ship accident can occur in many ways, including collision, capsize, fire, and other risks. These incidents not only result in significant human casualties but also encompass economic setbacks, disruptions in production, and environmental contamination. In a study conducted by Wrobel et al [17], accidents caused by ship navigation happened more than 85%, including grounding and ship collision. The probability is an essential data to predict the incoming event of collision risk, one of the studies is developed in Rawson and Brito [18] by using spatial collision risk assessment. The findings demonstrate that the degree of correlation between collisions and encounters varies not only across different types of vessels but also depending on the spatial scale of evaluation. The global maritime accidents also analysed in Xiao et al. [19] by developing framework using machine learning combined with spatial density analysis to analyse the trend of global maritime accidents in the range of 2001 to 2020. The trend shows fluctuations in range of 2001 to 2019, the significant decrease is illustrated at year of 2020, this can be assumed due to COVID-19, where trade activities were decreasing in number. The accidents that recorded are mostly caused by collision, stranding or grounding, and fire or explosion, constituting for 22.1%, 19.7%, and 16.7%, respectively. Other cause such as foundering, hull failure, and missing counts for 19.8%. While Capsizing, Machinery damage, and contact contributes respectively 7.8%, 7.7%, and 6.2%. Research from Fan et al. [20] examine the factors that impact navigational risk through the analysis of four operational phases, which encompass voyage planning, berthing and unberthing, port approach and departure, and open sea navigation.. The outcomes illustrated in Figure 4, Figure 5, and Figure 6 indicate that the phase characterized by Risk Influencing Factors (RIF) with the highest frequency pertains to open sea navigation. This phase encompasses all ship-related and environment-related RIF, along with the majority of human-related and environmental-related factors.

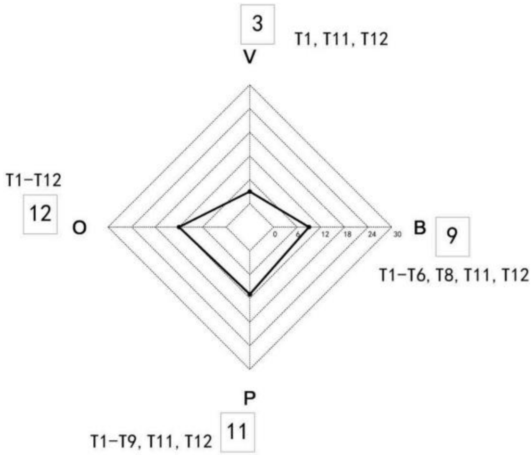

Figure 4. Distribution of technology factors during four operational phases [20]

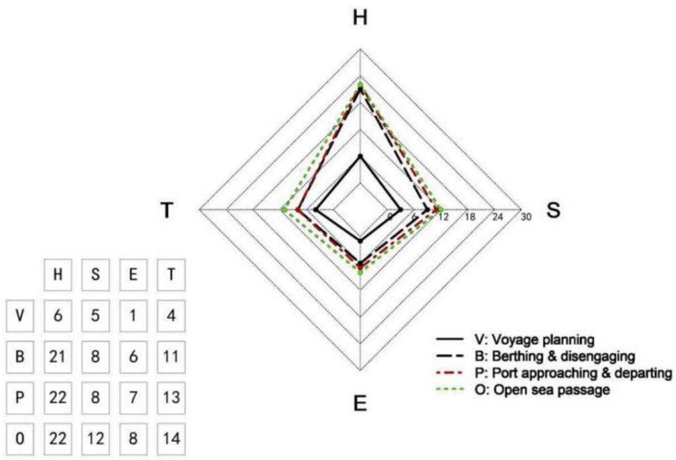

Figure 5. Distribution of four operational phases and four types of factors [20]

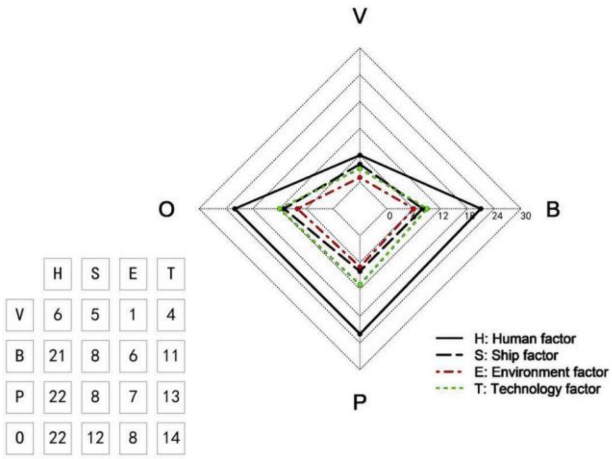

Figure 6. Breakdown of RIF per operational phase [20]

Human Factor is one factor that has been highly considered recently, particularly focusing on the analysis of the human element in certain incidents.The research of Qiao et al. [21] used the model and integrates the Human Factors Analysis and Classification System (HFACS), Fuzzy Fault Tree Analysis (FTA) and Artificial Neural Network (ANN) methodology to analyse the contribution of to assess the role of human errors in maritime accidents. The HFACS methodology was applied to identify and categorize human factors associated with 38 accidents. This information was then transformed into a Fault Tree structure, comprising Basic Events (BE), Intermediate Events (IE), and a Top Event (TE). The fuzzy analysis was utilized to assess the failure probability of the BE with expert input, while the ANN was constructed by aligning the BE, IE, and TE with variables in the input, hidden, and output layers, respectively. The findings indicate that the devised approach successfully addresses the limitations of the Fault Tree Analysis (FTA) method. In cargo port activities, the research of Khan et al. [22] investigate multifaceted human factor involvement accidents were investigated. This study investigated human factors contributing to hazardous cargo accidents in ports using Bayesian Network analysis. In normal circumstances, it was determined that the likelihood of such incidents stood at 21.47%, wherein factors such as organizational influence, execution challenges, safety considerations, suboptimal operations, cognitive factors, and rule violations played notable roles. The presence of evidence hinting at a potential hazardous cargo accident raised the probability of errors and rule violations contributing by an additional 5.06%.Conversely, evidence of errors and violations raised the overall accident risk by 8.51%. Sensitivity analysis identified errors and violations as the most critical factors, with a 48.2% impact on accident risk. Despite some limitations, this study provides practical insights to enhance port safety in hazardous cargo handling scenarios. In a study conducted by Cheng [23], the investigation revolves around the operational settings of Maritime Autonomous Surface Ships (MASS). This study integrates a human cognitive model into the System Theoretic Process Analysis (STPA) framework. The method is devised for both Remote Control Mode (RCM) and Remote Supervision Mode (RSM) scenarios, with a specific emphasis on analyzing collision and grounding incidents. The results show that the established approach can aid in the development of human-centered design and operational strategizing. In dynamic human reliability model research, Abaei et al [24] develop a framework to model the uncertainty of human performance factors. The framework takes into account hydrodynamic analysis of the structure and a subjective assessment of human activities across diverse weather conditions. Subsequently, a Dynamic Bayesian model is constructed to assess the time duration related to human performance. The outcomes reveal that this developed framework provides credible insights into the reliability of human performance during marine operations.

The task of designing, guiding, controlling, and maintaining offshore robotic vehicles has grown progressively more complex. To address this, Karimi and Lu [25] carried out research investigating guidance and control techniques applicable to marine vehicles. The survey results show recent advancements in fuzzy-based control design, neural network-based control design, dynamic surface control strategy, feedback control technique, and sliding model control method. These methodologies are primarily applied in tasks such as maneuvering, path following, trajectory tracking, formation control, and achieving consensus. Nevertheless, several research areas necessitate additional exploration, including aperiodic sampled-data control, control utilizing energy harvesting technology, management in the presence of measurement anomalies, control within the context of communication protocols, control susceptible to cyber-attacks, and fixed-time cooperative control for multiple marine vehicles.

Table 2. AI method and benefit for predicting ship accidents ship accidents and marine vehicle guidance and control

Author	Method	Benefit
Xiao et al. [19]	Machine learning combined with spatial density analysis.	Analyzing trends in global maritime accidents.
Qiao et al. [21]	Human Factors Analysis and Classification System (HFACS), Fuzzy Fault Tree Analysis (FTA), and Artificial Neural Network (ANN).	Analyzing human error contribution to ship accidents.
Khan et al. [22]	Bayesian Network analysis	Investigating human factors in hazardous cargo accidents.
Cheng [23]	STPA with human cognitive model	Studying maritime autonomous surface ship accidents.
Abaei et al. [24	Dynamic Bayesian model.	Modeling human performance in marine operations
Karimi and Lu [25]	Fuzzy-based control design.	Enhancing guidance and control of marine vehicles.
Karimi and Lu [25]	Neural network-based control design	Improving control methodologies for marine vehicles.
Karimi and Lu [25]	Dynamic surface control strategy.	Enhancing maneuvering and path following of marine vehicles.
Karimi and Lu [25]	Feedback control technique.	Improving trajectory tracking and formation control of marine vehicles.
Karimi and Lu [25]	Sliding model control method	Enhancing control methods for marine vehicles.

From that previous research, can be concluded that human factor which contribute to ship accidents can be analyse by various methodologies including usage of advance algorithm and machine learning. These factors are essential to consider the mitigation strategy and methodology to increase productivity and minimize its risk, Therefore, some AI are widely developed in maritime industries. Ship accidents occur due to various factors, with navigation-related incidents being the most common. Research efforts have led to predictive collision risk assessments and trend analysis of global maritime accidents. Human factors play a significant role, and innovative methodologies have been developed to analyze their contribution (Table 2). Additionally, research in hazardous cargo port operations, maritime autonomous surface ships, and dynamic human reliability modeling has provided valuable insights. Advances in guidance and control techniques for marine vehicles are evident, with some areas requiring further exploration, such as cyber-attacks and cooperative control. These studies collectively enhance our understanding of ship accidents and safety measures.

2.3 AI identifies risk in shipping community

Due to some challenges that increases in maritime field now days and in the future, and how to minimize risk that would be arise, advance technologies are developed. The developing of machine learning and Artificial Intelligence (AI) is increasing to answer those challenges. The AI is widely developed now days in every sector of industries due to its advantages, this also including in the maritime fields. Belows are AI that has been developing in the maritime fields to increase productivity and minimize risk.

Container shipping is a crucial aspect of the global economy, but it faces several risks, particularly amidst the COVID-19 pandemic. To better understand these risks, Zhou et.al. [26] conducted research using Bayesian Network Modelling. They used combined methodology that encompassed Failure Modes and Effects Analysis (FMEA), Evidential Reasoning (ER), and Rule-based Bayesian Networks (RBN) to prioritize the risks capable of affecting the resilience of container shipping services. The study discovered that economic risks pose the greatest threat, followed by political, technical, legal, social, and environmental risks, in that order. (Figure 7). Moreover, environmental risks were found to be the most sensitive to container shipping risk. The study also underlined the significance of social risks, which are related to sustainable shipping management, and are raised mainly by stakeholders' increasing scrutiny.

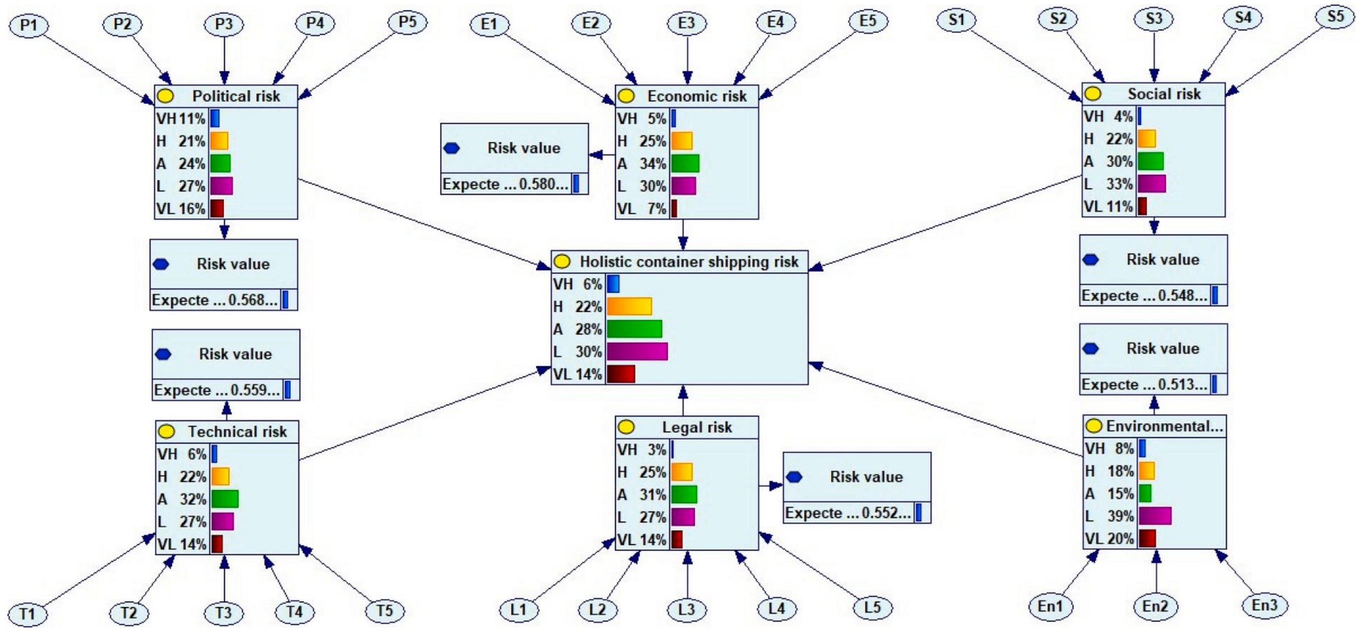

Figure 7. Bayesian network result of the holistic container shipping risk assessment model [26]

Islam et al. [27] aimed to enhance disaster readiness and response for coastal communities in the Eastern Atlantic region of Canada by harnessing AIS ship tracking data. They addressed a limitation of the AIS system, which doesn't provide details about the cargo quantity carried by each vessel. To overcome this, they used an artificial neural network to estimate cargo capacity based on vessel characteristics from historical AIS data. Their model attained a notably high level of predictive accuracy, with 'dimension to bow' emerging as the most significant contributing factor. The research underscored the significance of utilizing straightforward descriptive statistics derived from AIS data for disaster relief operation planning. This includes the examination of metrics such as standard deviation, mean, minimum, and maximum vessel capacities.

Table 3. AI methods and benefit for risk identification

Author	Method	Benefit
Zhou et al. [26]	Bayesian Network Modeling with a hybrid approach including FMEA, Evidential Reasoning, and Rule-based Bayesian Networks (RBN).	Identifying and ranking risks in container shipping
Islam et al. [27]	Artificial Neural Network (ANN) for estimating cargo capacity based on vessel characteristics from AIS data.	Improving disaster preparedness and response for coastal communities

In brief, global container shipping faces complex risks, particularly during COVID-19. Zhou et al. [26] used Bayesian Network Modeling to rank risks, finding economic risks to hold the highest importance, followed by political, technical, legal, social, and environmental risks, in that order. Environmental risks were notably sensitive. Islam et al. [27] improved disaster preparedness using AIS ship tracking data, estimating cargo capacity with an artificial neural network and highlighting the value of simple AIS statistics for relief planning. Table 3 shows the AI methods used in those scientific papers alongside the benefits of the application.

2.4 Ship′s navigation with AI Technology

2.4.1 Collision avoidance system

Navigation is important aspect in ship movement, this includes how to evade or avoid obstacles. The collision avoidance is developed to minimize collision risk. The research of Shaobo et al. [28], have worked on enhancing the decision-making process by designing a front-end component that offers preliminary information, with the back-end subsequently producing collision avoidance decisions. A multi-stage optimization decision model has been developed, taking into account various constraints such as maneuverability, multiple ships, COLREGS compliance, off-course conditions, and seamanship principles. This model is built on the modified velocity obstacle methodology. The findings indicate that the decision-making system for avoiding collisions is successful across a range of maritime situations. Figure 8 shows the framework of collision avoidance decision making system. Ni et al [29] conducted a study where they devised a methodology that utilizes an index approach and asymmetrical Gaussian fitting to evaluate collision risk. The encountering ships are classified into clusters using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. The proposed decision-making system is synthesized through a series of functional components, including data processing, conflict assessment detection, relevance analysis, action priority analysis, path planning, and performance monitoring. The outcomes reveal that the decision-making system demonstrate significant superiority in various maritime environment. In their work, Ni et al [30] have devised a multi-ship encounter scenario, integrating a distributed coordinated path planning algorithm with several constraints such as visual actions, temporal considerations, and the dynamic characteristics of the ships. In order to create a solution that is both pragmatic and compliant with COLREGs, a three-dimensional Generalized Velocity Obstacle (TGVO) is formulated. The findings indicate that a more in-depth analysis of ship avoidance maneuverability has been conducted to enhance the precision and applicability of optimization solutions.. In their study, Wang et al. [31] established a systematic mapping relationship between factors contributing to ship navigation risk and safety levels. They accomplished this by employing the fuzzy cognitive map method, which blends fuzzy and evidential reasoning. This fusion is employed to transform the initial variables and derive the strength of their associations, respectively. To refine the model, the algorithm of Non-linear Hebbian is used. The findings indicate that the created methodology possesses attributes of efficiency, agility, and robustness, which contribute to enhancing the safety dynamics of the ship's navigation system. In their study on path planning, Zhao et al [32], have devised a framework for path planning that incorporates multi-objective optimization and a sensory-vector replanning strategy. The results of this investigation reveal that through simulations and comparisons in diverse maritime scenarios, the proposed framework has proven its effectiveness and superiority.

In response to complex and dynamic environments, in another study, Zhao et al. [33] developed a hierarchical path planning method for unmanned surface vehicles. Their Adaptive Elite Genetic Algorithm with Fuzzy Inference (AEGAfi) combines adaptive fuzzy probability and elite selection pooling to optimize paths effectively, generating safe routes that quickly adapt to changing conditions. They implemented a local avoidance strategy, including compliant replanning mechanisms and transition paths, facilitating collision avoidance. Virtual sensory vectors seamlessly integrated global and local path-planning algorithms. Extensive simulations across diverse marine scenarios demonstrated the framework's effectiveness.

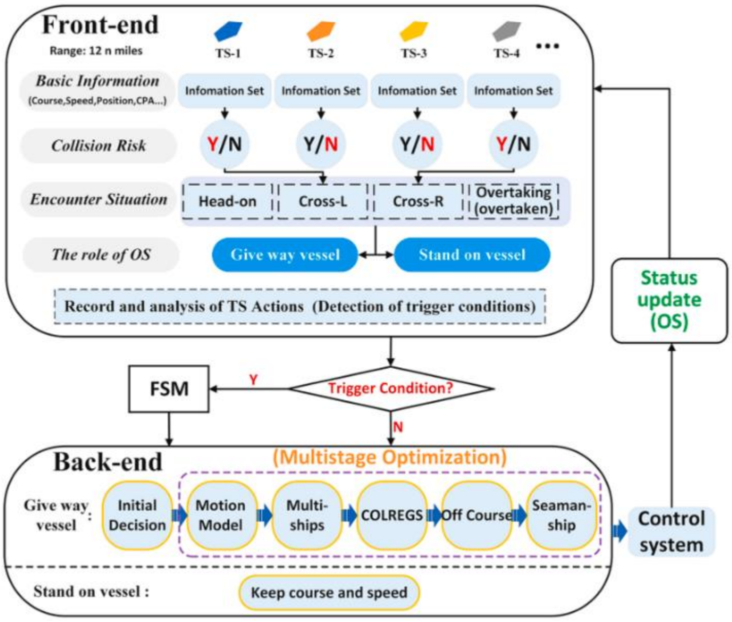

Figure 8. framework of collision avoidance decision-making system [28]

Gao and Shi [34] conducted a study on ship collision avoidance. Their study emphasizes the critical role of decision-making in ship handling for intelligent collision avoidance. It used AIS data and a ship encounter azimuth map to collect information on 12 ship encounter scenarios. A sliding window algorithm identified ship encounter behaviours for training. The research introduced the Seq-CGAN model, based on Seq2Seq, to generate collision avoidance decisions resembling human responses and streamline risk assessment. To enhance memory and adaptability, LSTM was combined with Seq-CGAN, trained on 2018 Zhoushan Port AIS data. Results confirm Seq-CGAN's efficacy in modelling ship handling sequences, contributing to maritime safety and efficiency. This approach holds promise for predictive frameworks in various intelligent systems, such as collision avoidance, route planning, and operational efficiency assessment.

Achieving real-time collision avoidance in multiple ships scenarios while considering ship maneuverability, collision risks, and COLREG compliance is a complex task. A study by Xie et al. [35] introduces a Model Predictive Ship Collision Avoidance approach, incorporating Q-learning, Beetle Swarm Antenna Search (BSAS), and neural networks. The study uses Model Predictive Control (MPC) for predictive collision avoidance strategies. The I-Q-BSAS algorithm combines improved BSAS and Q-learning to enhance MPC. A neural network creates an inverse model for real-time collision avoidance in MPC. Findings from simulations using the KVLCC2 model reveal that I-Q-BSAS outperforms BSAS and LDWPSO in typical encounters in terms of fitness and collision avoidance without significantly increasing time costs. The inverse model reduces time requirements while maintaining performance. In multi-ship collision avoidance, the enhanced method maintains a lower time cost than I-Q-BSAS and performs better in ship collision avoidance compared to the direct inverse model.

Detecting ships in maritime image sequences horizontally often leads to suboptimal performance due to misidentified background pixels. In a study by Chen et al. [36], an innovative method for ship detection that considers ship rotation angles is introduced. The authors have introduced a new method called Rotation Feature Decoupling Supported Deep Learning in their work. This approach utilizes a specialized model, named RYM, based on the You Only Look Once (YOLO) architecture. The RYM model is specifically designed for accurate and efficient detection of ships in maritime images, taking into consideration their rotation angles. It incorporates several components, including a rotation decoupled (RD) head, an attentional mechanism, and a bidirectional feature network (BiFPN) to effectively identify tilted ships. The RYM model demonstrates remarkable ship detection performance, achieving an average accuracy rate of 96.7%. Precision and recall metrics reach 93.2% and 94.7%, respectively. Furthermore, this framework is well-suited for real-time ship detection tasks, with a rapid processing speed of 45.6 frames per second (FPS).

Liu et al. [37] conducted a study to address energy consumption and communication range challenges in multiple unmanned surface vehicle (USV) operations. They introduced scheme for coordinating energy usage and a method for prioritizing tasks for efficient task allocation in multi-USV systems. Their research proposed a new self-organizing map (SOM)-based algorithm for multi-task allocation, which considers energy constraints and communication range. Additionally, a Fast Marching Method (FMM)-based path planning algorithm was integrated to ensure collision-free paths for USVs during maritime navigation.

Table 4. AI methods and benefit for collision avoidance and ship motion prediction

Author	Method	Benefit
Shaobo et al. [28]	Multi-Stage Optimization Decision Model with Modified Velocity Obstacle method.	Effective collision avoidance decision-making
Ni et al. [29]	Index Approach and Asymmetrical Gaussian Fitting with Density-Based Spatial Clustering of Applications with Noise (DBSCAN).	Risk collision assessment and decision-making.
Ni et al. [30]	Distributed Coordinated Path Planning Algorithm with Three-Dimensional Generalized Velocity Obstacle (TGVO).	Multi-ship encounter avoidance with COLREGs compliance.
Wang et al. [31]	Fuzzy Cognitive Map method	Assessing navigation safety countermeasures
Zhao et al. [32]	Multi-objective optimization and sensory-vector replanning.	Effective path planning in various ocean scenarios
Zhao et al. [33]	Adaptive Elite Genetic Algorithm with Fuzzy Inference (AEGAfi)	Hierarchical path planning for unmanned surface vehicles.
Gao and Shi [34]	Seq-CGAN model with LSTM.	Ship collision avoidance decision-making.
Xie et al. [35]	Model Predictive Control (MPC) with Q-learning and neural networks.	Real-time collision avoidance in multi-ship scenarios.
Chen et al. [36]	Self-organizing map (SOM) based algorithm.	Ship detection in maritime images considering ship rotation angles.
Liu et al. [37]	Self-organizing map (SOM) based algorithm.	Efficient task allocation in multi-unmanned surface vehicle systems.
Mingyang et al. [38]	Multiple-Output Gaussian Process Regression (MOGPR).	• Benefit: Predicting ship motion dynamics and grounding risk

In summary, navigation and collision avoidance are pivotal aspects of ship movement to ensure maritime safety and efficiency. Several research studies have contributed significantly to this field by developing advanced decision-making systems, risk assessment methodologies, and path planning frameworks (Table 4). These innovations collectively enhance our ability to prevent collisions, assess navigational risks, and optimize ship routes, ultimately improving maritime safety and operational effectiveness. Additionally, the integration of intelligent technologies and adaptive algorithms holds promise for addressing complex and dynamic maritime scenarios, including multi-ship encounters and unmanned surface vehicle operations.

2.4.2 Ship motion prediction

In the study conducted by Mingyang et al. [38], motion prediction is investigated through a process that involves grouping environmental factors. This is achieved by creating a hybrid approach that combines the K-means and DB-SCAN (Density-Based Spatial Clustering of Applications with Noise) big data clustering methods, along with Principal Component Analysis (PCA). The prediction of specific ship motion dynamics is carried out using the Multiple-Output Gaussian Process Regression (MOGPR) method, with a focus on modeling time-varying ship maneuvers along various routes, particularly in terms of surge accelerations. Operational conditions are simulated using data sources such as the Automatic Identification System (AIS), General Bathymetric Chart of the Oceans (GEBCO), and up-to-the-minute hydro-meteorological data records. The identification of ship center-line trajectories along predefined paths is accomplished through the application of a Dynamic Time Warping (DTW) method. The results of this methodology reveal its potential to aid in predicting the probabilistic distribution of ship dynamics and grounding risk. Figure 9 illustrates the framework for using machine learning to predict ship motion trajectories.

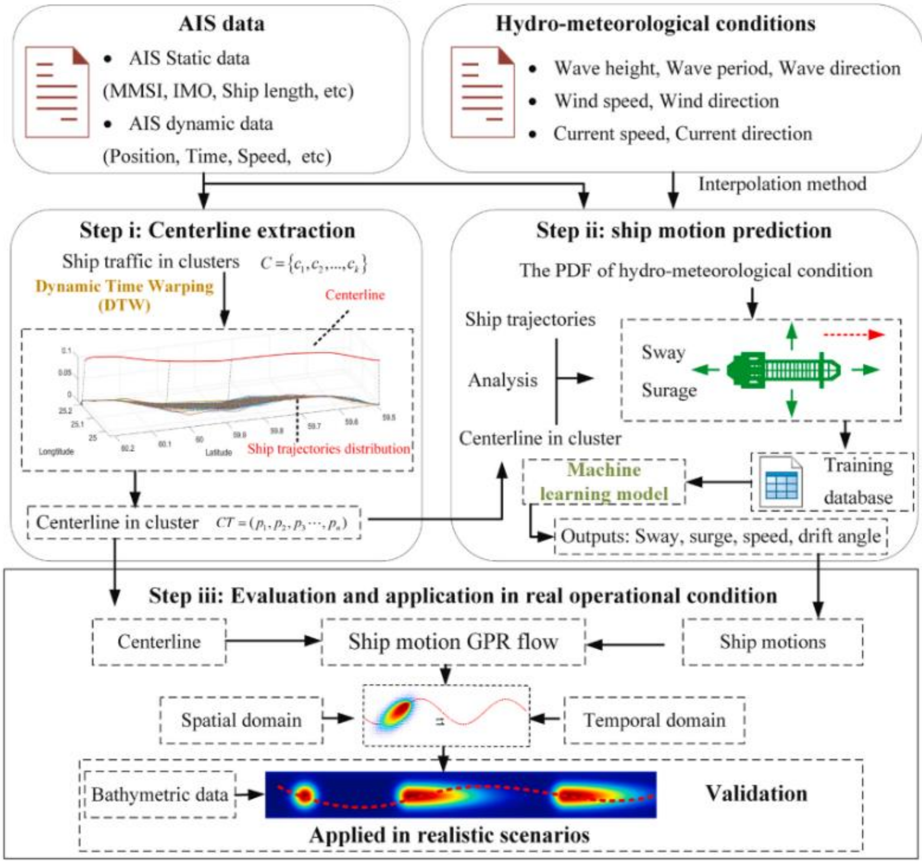

Figure 9. Framework for the prediction of ship motion trajectories by machine learning [38]

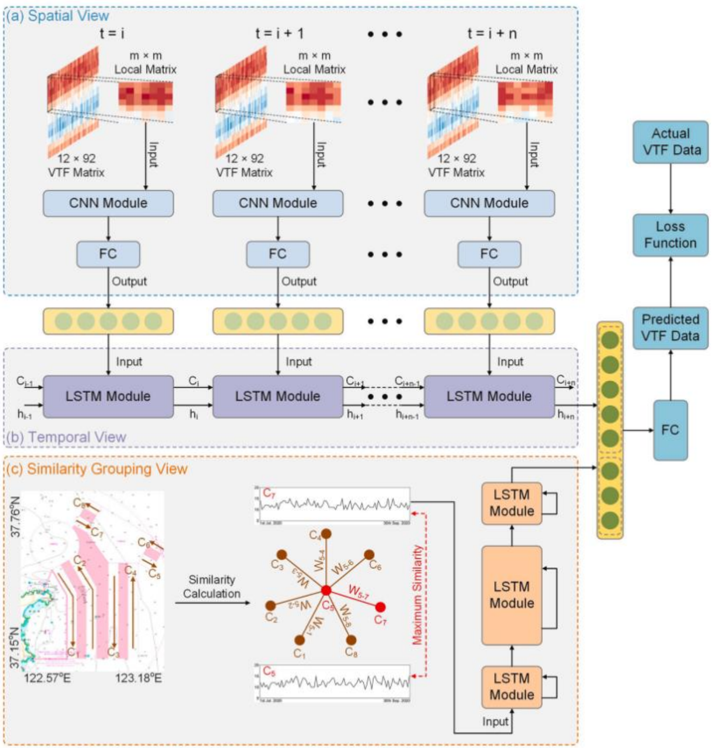

Figure 10. The flowchart of the Improved CNN-LSTM Network prediction method [39]

2.4.3 Vessel traffic and trajectory prediction

Li et al. [39] tackles the challenging task of enhancing Vessel Traffic Flow (VTF) accuracy using big data from Automatic Identification Systems (AIS). They achieve this by developing learning-based prediction networks that enhance Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models through similarity clustering. CNN is employed for spatial information, while LSTM captures temporal patterns, effectively converting the original one-dimensional data into a matrix format (hours of the day × days) to suit the proposed methodology's input. The results show that the developed methodology exhibits prediction accuracy and stability performance. Figure 10 illustrates the Enhanced

CNN-LSTM Network. In their review, Ribeiro et al. [40] examine the utilization of constraints and the challenges involved in detecting anomalies in maritime traffic. This research studying the detection of suspicious activities which could be used in the surveillance programs. This research addresses challenges related to managing large datasets, inconsistent data, irregular updates, and dynamic data. The review of this study emphasizes the development of approaches that concentrate on various forms of anomaly detection, with a particular focus on ship kinematic data derived from the Automatic Identification System (AIS), including ship location, Speed Over Ground (SOG), and Course Over Ground (COG).

Yang et al. [41] conduct a research about geographical spatial analysis and risk prediction using machine learning techniques for maritime traffic accidents occurring in the Fujian sea area. The study involves an analysis of the relationship between accident frequency and traffic characteristics within grid areas. Various machine learning models, such as the Random Forest, Adaboost, GBDT, Stacking combined model, traditional SVM, and deep learning models like CNN and LSTM, are employed and compared. The analysis reveals that the Fujian sea area exhibits distinct clustering patterns and positive spatial correlations. Kernel density estimation highlights subareas, including Ningde, Fuzhou, and Xiamen, with high accident density and the greatest risk across the entire Fujian sea area. High-high accident clustering is primarily observed in Ningde and Fuzhou, while Xiamen, Putian, and Zhangzhou exhibit low-low clustering. In terms of prediction, the Stacking combined model surpasses other models with high accuracy, precision, recall, and F1-score values. For predicting accident-prone areas, it achieves values of 0.912, 0.910, 0.912, and 0.904, while for accident severity prediction within grid areas, it scores 0.750, 0.745, 0.750, and 0.746. These results demonstrate its superior performance in predicting maritime traffic accidents.

Kanazawa et al. [42] study explores how physics-based models and data can work together in a cooperative model for ship trajectory prediction. They use a cooperative model that combines a physics-based model with a data-driven compensator to predict ship trajectories accurately. Their simulations test various physics-based models, including some with uncertainty, and find that a balance between model accuracy and data availability is crucial for cooperative model performance. While a diverse set of physics-based models can help with model identification, but overly inaccurate models disrupt training. In practical experiments, they validate that the combination of a modified physics-based model with a limited dataset can result in the development of accurate ship dynamic models.This method presents a viable solution for mitigating time and cost constraints within the cooperative framework. The research underscores the significance of striking a balance between physics-based models and data to create efficient cooperative models for predicting ship trajectories, providing a practical solution applicable to real-world projects.

The volatile bulk shipping industry faces challenges due to incomplete information in a decentralized spot market. Yin et al. [43] created a method using AIS data to address this. It combines a static Bayesian neural network (BNN) model with a dynamic trajectory model for accurate ship destination prediction. This study offers three key contributions. Firstly, the stacking method combines static and dynamic models for increasingly precise predictions as more trajectory data becomes available. Secondly, a constrained linear regression approach reveals alterations in the influence of static and dynamic elements in the stacking outcomes. Initially, the trajectory model's weight is low, but it significantly increases with more data. Thirdly, a modified DBSCAN clustering method streamlines trajectory analysis and serves as a reference for route adjustments during a vessel's journey.

Table 5. AI methods and benefit for Vessel Traffic and Trajectory Prediction

Author	Method	Benefit
Li et al. [39]	Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) with similarity clustering	Accurate prediction of vessel traffic flow
Ribeiro et al. [40]	Anomaly detection for ship kinematic data from AIS.	Detection of suspicious activities and anomalies in maritime traffic
Yang et al. [41]	Machine learning models such as Random Forest, Adaboost, GBDT, and Stacking	Predicting maritime traffic accidents and risk assessment.
Kanazawa et al. [42]	Cooperative model integrating physics-based and data-driven approaches.	Accurate ship trajectory prediction by combining physics-based and data-driven models.
Yin et al. [43]	Static Bayesian Neural Network (BNN) model with a dynamic trajectory model.	Accurate ship destination prediction in the bulk shipping industry

In summary, research in Vessel Traffic Flow (VTF) analysis using AIS data faces challenges but offers solutions. Innovative prediction networks with CNN and LSTM, anomaly detection in maritime traffic, and risk prediction using machine learning models have all improved safety and accuracy. Cooperative ship trajectory prediction models balance physics-based and data-driven approaches, while AIS-based methods enhance bulk shipping industry insights. These studies collectively advance maritime traffic management and trajectory prediction (Table 5).

2.5 Safety in design with AI Technology

In the terms of safety and design, there are some research which discuss and involve AI. Siqueira et al. [44] introduces a Bayesian approach that relies on population variability to estimate accident rate distributions. This method utilizes data derived from expert opinions to assist in risk assessments and furnish decision-makers with valuable insights for improving accident prevention measures and risk reduction strategies. Figure 11 shows the Bayesian Population Variability Analysis.

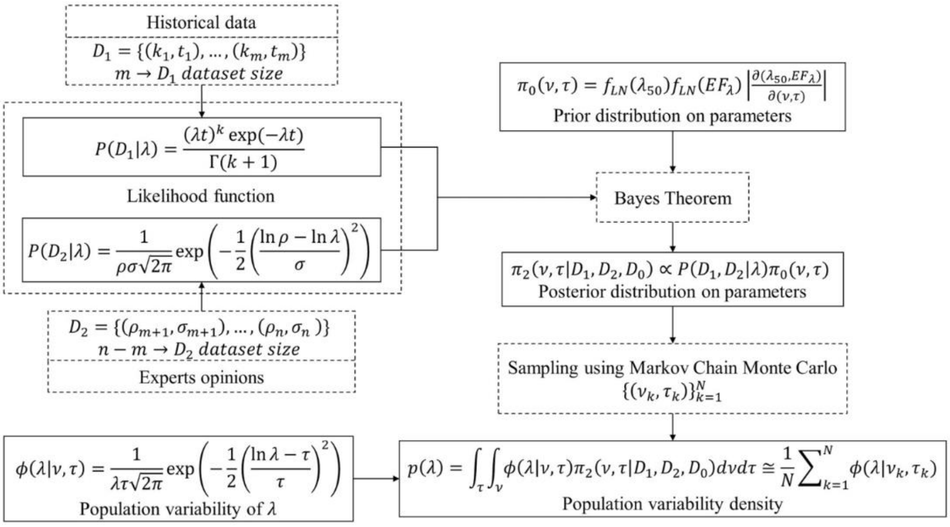

Figure 11. Bayesian population variability analysis [44]

Zhang et al. [45] introduce a predictive analytics approach that employs the Lempel-Ziv algorithm and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) for enhancing traffic safety management. The methodology is develped into three parts including Pre-processing, Quantification of traffic flow, and complexity ranking. Figure 12 shows the framework of traffic flow complexity metric estimation. High complexity indicates that ship travel time sequences are influenced by traffic encounter patterns rather than exhibiting periodic or stochastic behavior. Greater traffic flow complexity can lead to an elevated occurrence of undesired events.

Dreany and Roncace [46] conducted a study to evaluate the safety of an architectural system, focusing on a real-world safety-critical application, specifically, an unmanned surface vehicle (USV). This safety analysis encompassed both simulated and real nautical environments. The primary objective was to establish a safety plan for a cognitive architecture. This safety design was developed using a method that identified and mitigated hazards associated with a USV controlled by such an architecture. The outcome of this analysis was a structured, task-oriented framework for communicating safety requirements, a crucial step in ensuring the secure operation of the USV by minimizing risks to both personnel and equipment.

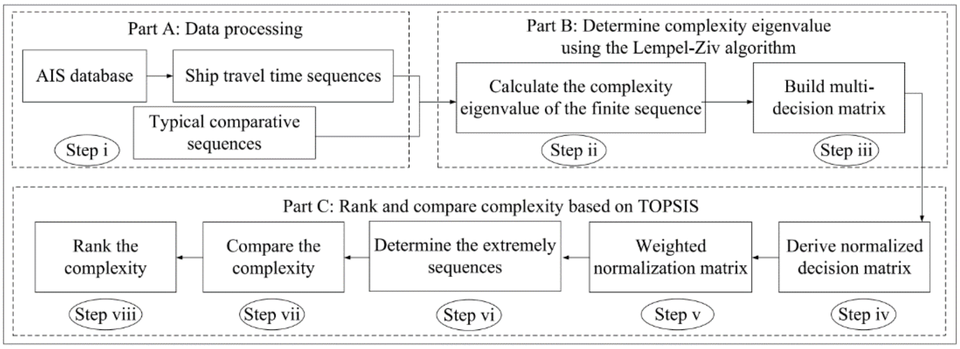

Figure 12. Framework of traffic flow complexity metric estimation [45]

Vairo et al. [47] conducted a study on solid oxide fuel cells in shipping. Machine learning model is used to detect system deviations early, addressing concerns about emissions and environmental impact in the shipping industry. Electrochemical Impedance Spectroscopy (EIS) helped identify hydrogen leaks and oxygen concentrations in cells, crucial for safety. Detecting gas leaks early prevents potential accidents. Incorporating physics into machine learning models enhances their reliability and interpretability, improving their performance beyond their training data.

The second-hand vessel market operates differently from the new-building vessel market, and it involves complex and conflicting criteria, adding uncertainties into the process of selecting a ship. Görçün et al. [48] conducted a study on selecting suitable Ro-Ro Vessels in the second-hand market using the Bonferroni approach within the framework of WASPAS in a type 2 neutrosophic fuzzy environment. Their analysis identified Trailer Lane length as the most influential factor. The study verified the results' consistency and validity through stability and robustness checks, establishing that the proposed T2NN WASPAS'B model is reliable for making rational decisions.

In an effort to combat greenhouse gas emissions, the IMO has put in place regulations aimed at reducing shipping emissions by 40% by 2030 in comparison to 2008 levels. These measures, including the Efficiency Existing Ship Index (EEXI) and the Annual Operational Carbon Intensity Indicator (CII), took effect on January 1, 2023. In this context, a study by Díaz-Secades et al. [49] focuses on a waste heat recovery system for marine engines. This system efficiently captures waste energy, providing economic advantages, minimizing pollution, and generating fresh water. The study uses Bayesian optimization to find optimal waste heat recovery states. However, establishing an evaluation function for optimization is challenging due to trade-offs among key indicators. To overcome this, the study proposes a preference learning procedure based on expert knowledge to create a suitable function for Bayesian optimization. When implemented in an engine case study, the system achieves a significant 15.04% reduction in fuel consumption, leading to improved energy efficiency indicators: a 6.98% drop in EEXI and a 13.85% reduction in CII.

Table 6. AI methods and benefit for safety and design

Author	Method	Benefit
Siqueira et al. [44]	Bayesian approach utilizing population variability	Estimating accident rate distributions and enhancing risk assessments.
Zhang et al. [45]	Lempel-Ziv algorithm and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS).	Traffic safety management and complexity ranking
Dreany and Roncace [46]	Safety Analysis of Cognitive Architecture	Establishing safety blueprints for cognitive architectures and unmanned surface vehicles (USVs).
Vairo et al. [47]	Machine learning model.	Detecting deviations in solid oxide fuel cell systems for safety
Görçün et al. [48]	Bonferroni approach within the framework of WASPAS	Selecting suitable Ro-Ro vessels in the second-hand market.
Díaz-Secades et al. [49]	Bayesian optimization with preference learning	Reducing greenhouse gas emissions and improving energy efficiency.

In summary, the maritime industry is increasingly integrating AI and advanced technologies to enhance safety and design. Research efforts encompass Bayesian methods for accident rate estimation, predictive analytics for complex traffic safety management, safety assessments of cognitive architectures, early system deviation detection with machine learning, rational decision-making criteria for vessel selection, and innovative waste heat recovery systems (Table 6). These initiatives collectively contribute to safer and more efficient maritime operations, aligning with environmental regulations and sustainability objectives in the industry.

2.6 Port activity with AI

In port-related activities, there are studies that discuss the development of AI, including review papers that identify the application of AI or the development of AI technology to be implemented in port activities. Zarzueloa et al. [50] conducts a literature review on Industry 4.0 technologies in the port and maritime industry, focusing on smart ports and Ports 4.0. It identifies key keywords and combinations, resulting in 168 potential research areas. Notably, while Simulation and Modelling (S&M) and Automation have mature academic coverage, other Industry 4.0 elements lack in-depth research and are often based on practical experiences reported by industry professionals. IoT and sensing solutions, along with Horizontal and Vertical System Integration (HVSI) in Terminal Operating Systems, are leading the adoption of these technologies. However, challenges related to cybersecurity and data sharing are hindering their widespread use. Geographically, Europe and Asia's large ports are ahead in embracing Industry 4.0, while America and smaller ports are lagging. Investment barriers may play a role, but increasing accessibility is expected to drive wider adoption as more participants join Industry 4.0 projects in the port and maritime industry, fostering collaboration and implementation.

Filom et al. [51] conducted a comprehensive systematic literature review on this subject. Their aim was to examine previous research from various angles, including the field of application, the type of application, the machine learning method, the data used, and the geographical location of the study. The yearly count of articles in this domain has seen a steady rise, with the predominant application of machine learning methods being the prediction of various port features. Additionally, recent literature reveals the emergence of novel applications involving machine learning, particularly in prescriptive and autonomous contexts. Moreover, the research has pinpointed gaps and challenges while also addressing future research directions, considering both method-focused and application-centered perspectives.

Miętkiewicz's [52] study delves into the potential threats that arise in the surface, underwater, and aerial areas surrounding Polish Baltic LNG/FSRU terminals. These threats are dynamic and surreptitious in nature, leaving little time for response. The paper introduces a suggestion for a modular surface Unmanned Surface Vehicle (USV), as illustrated in Figure 13. This USV can function as a foundational framework for task-specific systems employing Unmanned Underwater Vehicles/ Remotely Operated Vehicles (UUV/ROV) and UAV technologies. This proposed solution offers an innovative method for addressing the challenge of deploying autonomous systems to secure LNG/FSRU terminals. It opens up opportunities for monitoring the conditions in the regions surrounding the terminals, including the establishment of buffer zones, overseeing the routes leading to the terminals, and potentially providing support such as protection and escort services for LNG tankers within territorial waters.

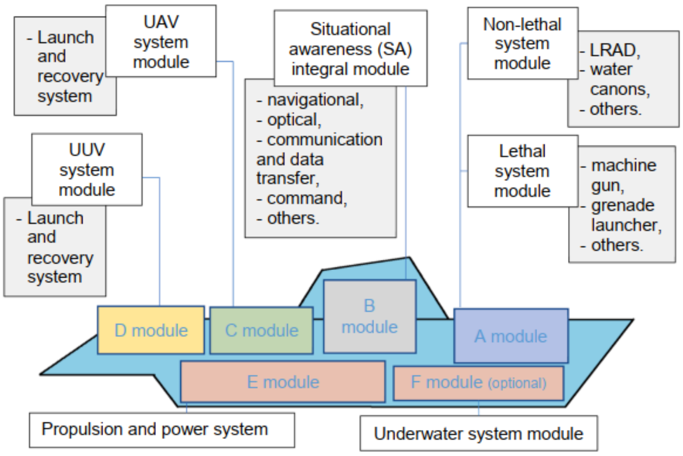

Figure 13. Proposal of task modules implemented by an unmanned surface vehicle [52]

Khan et al. [53] conducted an investigation focused on assessing the risks associated with the docking of hazardous cargo vessels, employing Bayesian networks. They employed a combination of binary logistic regression and expert judgment to identify key factors, utilizing a Bayesian network for their analysis. The findings reveal that, under typical conditions, the probability of risk associated with hazardous cargo vessels is relatively low at 3.97. However, the risk score suggests that it still demands attention. Environmental factors were identified as the most significant contributors, with the potential to elevate the accident probability to 14.91 and a high-risk score of 9.17, indicating an urgent need for action. The study underscores the significance of prioritizing factors such as crew training, crew mental state, wind force, water velocity, channel width, berth layout, and port location to ensure the safe berthing of hazardous cargo vessels.

Table 7. AI Methods for port activity improvement

Author	Benefit	Method
Zarzuelo et al. [50]	Identifying key areas and trends in the application of Industry 4.0 technologies in the port and maritime industry.	Literature review and analysis of keywords and research areas.
Filom et al. [51]	Analyzing previous research on machine learning applications in ports and identifying gaps and challenges.	Systematic literature review and analysis of machine learning methods and applications.
Miętkiewicz [52]	Proposing a modular USV system for monitoring and securing LNG/FSRU terminals.	Design and development of an autonomous USV
Khan et al. [53]	Assessing the risk associated with berthing hazardous cargo vessels and identifying key contributing factors.	Bayesian networks combined with logistic regression and expert judgment.

In summary, research in port-related activities demonstrates the growing influence of AI and Industry 4.0 technologies. These innovations are reshaping smart ports and maritime operations, with a focus on prediction, security, and risk assessment (Table 7). While some areas receive extensive research attention, others remain relatively unexplored, presenting opportunities for future advancements. The maritime industry's adoption of these technologies varies by region, with Europe and Asia leading the way. Despite challenges such as cybersecurity and data sharing, the momentum toward Industry 4.0 in ports is expected to grow, fostering collaboration and implementation for enhanced efficiency and safety.

3. Challenges and Obstacles

Despite the numerous advantages associated with integrating AI technology into the shipping industry, there are substantial challenges and obstacles that must be addressed. One critical obstacle is the limited quality of available data, as AI systems rely on consistent, accurate, and reliable data for optimal performance. To overcome this challenge, efforts should be directed towards enhancing data quality through improved collection, validation, and maintenance processes. Another significant concern in the shipping sector is cybersecurity. The industry is vulnerable to cyber threats, making it imperative to implement robust cybersecurity measures. This includes advanced encryption protocols and comprehensive training programs to fortify the resilience of AI-integrated systems against potential disruptions caused by cyberattacks.

Moreover, there is a noticeable research gap regarding the use of AI to enhance safety in passenger ships. This gap presents a unique opportunity for focused exploration and development of AI technology specifically tailored for passenger vessels. Redirecting research efforts toward this unexplored area not only has the potential to elevate safety standards for passenger ships but also promises to drive innovation and technological advancement in the maritime industry. In summary, while the integration of AI holds promise for the shipping industry, addressing challenges related to data quality and cybersecurity is crucial. The underexplored realm of AI applications in passenger ship safety provides an opportunity for further research and development, with the potential to revolutionize safety measures and reshape the technological landscape of maritime operations.

4. Conclusion

In conclusion, the field of ship accidents has seen significant research efforts, shedding light on various contributing factors, especially navigation-related incidents. These studies have yielded predictive collision risk assessments, global accident trend analysis, and a deeper understanding of human factors. Additionally, research in hazardous cargo port operations, maritime autonomy, human reliability modeling, and guidance/control methodologies for marine vehicles has enriched our knowledge. Global container shipping faces multifaceted risks, with economic and environmental factors at the forefront. Innovative methodologies like Bayesian Network Modeling and AIS-based cargo capacity estimation are helping mitigate these risks.

Navigation and collision avoidance remain crucial for maritime safety, and recent research has advanced decision-making systems and risk assessment methodologies. The integration of intelligent technologies and adaptive algorithms holds promise for addressing complex maritime scenarios. In various domains, including ship motion prediction, Vessel Traffic Flow analysis, maritime safety, and port-related activities, AI and advanced technologies are making significant strides. These innovations are reshaping the maritime industry, enhancing safety, efficiency, and sustainability. The most frequently utilized AI technology in maritime traffic analysis and risk prediction studies is Bayesian Network Modeling, with a focus on assessing and ranking various risks affecting maritime operations. Additionally, Machine Learning techniques, including models such as Random Forest, Adaboost, GBDT, Stacking, SVM, CNN, and LSTM, are widely employed for diverse applications in this domain. Other AI technologies, such as Fuzzy Logic, Artificial Neural Networks (ANN), and Control Techniques, are also frequently used to address specific challenges in maritime traffic analysis and risk assessment. In summary, the maritime industry is embracing AI and Industry 4.0 technologies, particularly in smart ports and maritime operations.

It's interesting to note that while some areas of the maritime industry receive more attention than others, there's been a rising adoption of new technologies despite challenges such as cybersecurity and data sharing. These advancements are expected to improve efficiency and safety throughout the sector. In fact, electronic research suggests that there hasn't been much exploration into using AI to enhance passenger ship safety, which could be an important area of study in Indonesia. Previous studies have explored various AI technologies and methods for maritime collision avoidance, including Bayesian Network Modeling, Artificial Neural Networks, Machine Learning, Fuzzy Fault Tree Analysis, and more. These methods could potentially be adapted for use in passenger ships. It's also important to note that there's a growing need for research into AI technology to prevent fires on ships and avoid capsizing.

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