Dynamic Risk Assessment for New Types of Ro-Pax Ferries

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Advancements in maritime technology, expanding traffic, and stricter environmental standards present increasing challenges for operating RO-PAX vessels. Traditional risk assessment methods remain static and retrospective, which makes them ineffective for addressing the evolving complexities of navigational hazards in current RO-PAX vessels. The transition to predictive risk assessments that operate in real-time becomes essential to address modern navigation challenges. Researchers plan to create a complex dynamic risk assessment (DRA) model that will address the specific needs of modern RO-PAX vessels. The model combines operational, environmental, and technical data inputs to deliver real-time navigation and port operations risk analysis. The model aims at improving risk assessment precision and response time through machine learning techniques and Big Data analytics. The model will use machine learning to analyse previous incidents and adjust its algorithms based on new information. Big Data analytics will supply essential computational power for processing the extensive data generated by maritime operations. Implementing these technologies will improve safety measures at sea, alongside operational performance.

KEYWORDS

~ Dynamic Risk Assessment (DRA)
~ Vessel safety
~ Machine learning
~ RO-PAX

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1. INTRODUCTION

RO-PAX vessels are vital components within transportation infrastructure, while maritime transport remains essential for global trade. The growing transportation numbers of passengers and cargo on these ships introduce industry challenges related to operational efficiency and, more importantly, safety considerations. RO-PAX ship accidents have severe repercussions, affecting monetary interests and human safety. According to Eurostat data, passenger maritime transport increased by 50% in 2022 compared to 2019, highlighting the urgent need for effective risk management tools. Statistics indicate maritime accidents, including collisions and technical failures, responsible for financial losses and human suffering. Therefore, it is essential to develop modern tools for assessing and managing risks considering dynamic changes in the operational environment.

Current static risk assessment methods are inadequate for evaluating the safety of ship manoeuvring. Their limitations in considering dynamic conditions, such as sea currents and wind, and their failure to account for the crew's and systems' reaction times can lead to erroneous conclusions. Based on established scenarios, these methods fail to reflect real emergencies and do not consider advanced automation systems. The subjectivity of assessments and the issue's complexity indicates the urgent need for more dynamic approaches to risk evaluation. This research is not just important; it is necessary.

This work presents the foundations for developing a dynamic navigation risk model that considers the vessel's variable technical parameters and the waterway's hydrodynamic conditions. This model could significantly improve the safety of RO-PAX ship manoeuvres. In the context of the increasing volume of maritime transport and changing safety regulations, the impact of this research could be profound, potentially saving lives and reducing financial losses.

2. LITERATURE REVIEW

The article (Duijm 2015) discusses risk matrices in risk management, highlighting their prevalence in various standards and corporate risk acceptance criteria. It addresses the recently recognised weaknesses of risk matrices, aiming to explore these issues and offer recommendations for their design and application. The paper reviews the existing literature on the topic and presents the author's observations, with a view to reinforcing and expanding on current recommendations. Key issues discussed include the relationship between risk matrix colouring and risk definitions, the subjective assessment of likelihood and consequences, the scaling of categories, and the use of corporate risk matrix standards. Additionally, the paper proposes a probability-consequence diagram with continuous scales as an alternative to traditional risk matrices. In the article (Shannaq et.al. 2024), the author discusses research on developing and evaluating machine learning models that predict budget overruns in completed projects. The study utilised a dataset of 177 projects, considering environmental risks, employee skill levels, safety incidents, and project complexity. Specifically, the author analyses various machine learning models, including Neural Networks (MLP), Support Vector Machines (SVM), Ridge Regression, Lasso Regression, and Random Forests. It was noted that the MLP model significantly improved its performance after hyperparameter tuning, while other models showed minimal changes in their results. The author also highlights the limitations of specific models and identifies areas for further research to enhance risk assessment in organisational policies. The article (Zeng, Yang, i Zhang 2014) presents a methodology utilising Bayesian Networks (BN) for risk analysis in RoPax transport. It begins by constructing a BN model based on data collection and expert surveys to analyse sailing risks. The paper details the design of the Expectation Maximisation (EM) algorithm for parameter learning and the Evidence Prepropagation Importance Sampling (EPIS) algorithm for reasoning. A sensitivity analysis is also performed. A case study of the RoPax system in the Bohai Gulf, China, validates the model, showing that the BN approach effectively addresses data deficiencies and incident interdependencies, while providing decision support for risk mitigation. The article (Borjalilu 2024) addresses the challenges of implementing safety management systems in extensive operational domains. It highlights the lack of effective methods in the current literature for utilising expert subjective inferences to analyse data and predict the performance of safety and quality management systems. The paper emphasises the potential of machine learning, a subset of artificial intelligence, to enhance safety management by improving efficiency, reducing costs, and fostering better decision-making. It notes that abundant data in operational sectors challenges machine learning implementation. The study proposes the creation of a safety data pool to assess, analyse, and predict safety outcomes, ultimately recommending machine learning methods for risk management in operational domains. The article (Hsu et.al.2022) discusses a risk assessment of navigation safety for ferries. It begins by investigating risk factors (RFs) related to ferry navigation safety through literature and operational features. A fuzzy Analytic Hierarchical Process (AHP) approach is proposed to assign weights to these RFs, followed by developing a continuous risk-matrix model to evaluate their risk levels. An empirical study of ferries operating across the Taiwan Strait is conducted to validate the model. The findings provide practical insights for ferry operators to enhance safety performance and suggest that the proposed risk assessment approach can improve navigation safety. The article (Kuzlu, Fair, and Guler 2021) reviews the increasing use of the Internet of Things (IoT) and the accompanying rise in cybersecurity concerns. It highlights the role of Artificial Intelligence (AI) in developing complex algorithms to protect networks and IoT systems. However, it also notes that cyber-attackers have begun to exploit AI, using adversarial AI to conduct attacks. The paper compiles information from various surveys and research studies on IoT, AI, and related cyber-attacks to summarise and present the interconnections between these topics comprehensively.

The article (Hsu i Kao 2021) focuses on the safety of ship berthing operations at port docks. It begins by investigating these operations' safety factors (SFs). A gap assessment model using the Fuzzy Analytic Hierarchical Process (AHP) is proposed to evaluate the perceived differences in safety factors between port marine pilots and shipmasters. The practical application of the model is illustrated through a study of ship berthing operations at Kaohsiung Port in Taiwan. The findings provide insights for marine pilots and shipmasters to enhance the safety performance of ship berthing operations at port docks.

3. PROPOSED METHODOLOGY

The International Maritime Organisation (IMO) introduced the Formal Safety Assessment (FSA) procedures for evaluating safety risks to enhance maritime safety. As illustrated in Fig. 1, this process consists of five stages: (1) identifying hazards, (2) analysing risks, (3) exploring risk control options, (4) conducting a cost-benefit analysis, and (5) providing recommendations for decision-making. (Hsu i in. 2022)

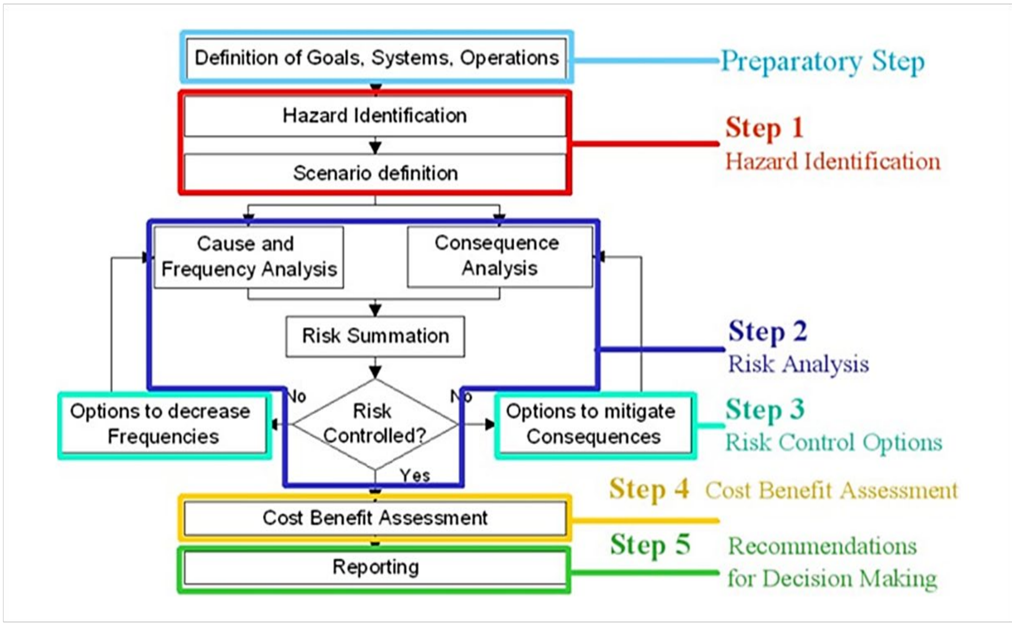

Figure 1. The Formal Safety Assessment (FSA) procedures (Hsu et.al. 2022)

Impact →

Likelihood ↑	Negligible	Minor	Moderate	Significant	Severe
Very Likely	Low Med	Medium	Med Hi	High	High
Likely	Low	Low Med	Medium	Med Hi	High
Possible	Low	Low Med	Medium	Med Hi	Med Hi
Unlikely	Low	Low Med	Low Med	Medium	Med Hi
Very Unlikely	Low	Low	Low Med	Medium	Medium

Figure 2. Example of risk matrix

Traditionally, a risk matrix is constructed based on the consequence and likelihood of the risk factor (RF). The consequence represents the potential loss the shipowner may face when a specific RF occurs, and it is typically categorised into 1 to 5 levels, such as very serious, significant, moderate, and minor. The likelihood indicates how often a particular RF happens within a defined timeframe, also divided into 1 to 5 levels, such as frequently occurring, common, occurrring less often, and rarely occurring. (Hsu i in. 2022). In a traditional risk matrix, the levels of consequence and likelihood are used to create a two-dimensional grid that ranks the RFs. This grid is segmented into various coloured zones to represent different risk levels. The risk value is determined by multiplying the two levels together. RFs in the green zone, with risk values ranging from 1 to 2, are classified as low risk (L). Conversely, RFs in the yellow and red areas are categorised as medium risk (M) and high risk (H). Since both consequence and likelihood levels are discrete, the resulting risk value is also discrete, making the panel a discrete risk matrix. In the FSA procedures, Step 1 involves identifying hazards by defining the RFs, and a risk matrix is typically utilised in Step 2 for risk analysis. Traditionally, this matrix is structured based on the consequence and likelihood of each RF. (Duijm 2015) In practice, the discontinuous nature of a risk matrix can hinder its effectiveness in terms of accuracy, influenced by factors such as the reliability of measurement data and the grading of the risk matrix.(Hsu and Kao 2021). A continuous risk matrix has been proposed to mitigate these discontinuity issues, as depicted by the curve in Figure 2 (Hsu et.al. 2022).

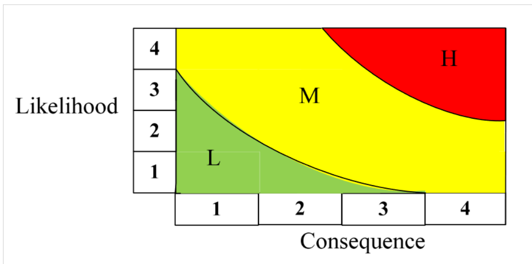

Figure 3. The continuous risk matrix (Hsu et al. 2022)

Based on the above, it should be assumed that a continuous risk matrix is more suitable for assessing the safety of manoeuvring RO-PAX vessels.

4. KEY ELEMENTS OF THE RESEARCH PROBLEM

Below, the key elements of the research problem have been defined:

Identification of Hazards During Manoeuvring: Operational factors (e.g., speed, course), technical parameters (e.g., number and type of propellers and propulsion type, frequency and consequences of technical failures), and environmental conditions (e.g., currents, wind, water level/state, visibility), as well as the crew's experience, have the most significant impact on the risk during maneuvering.

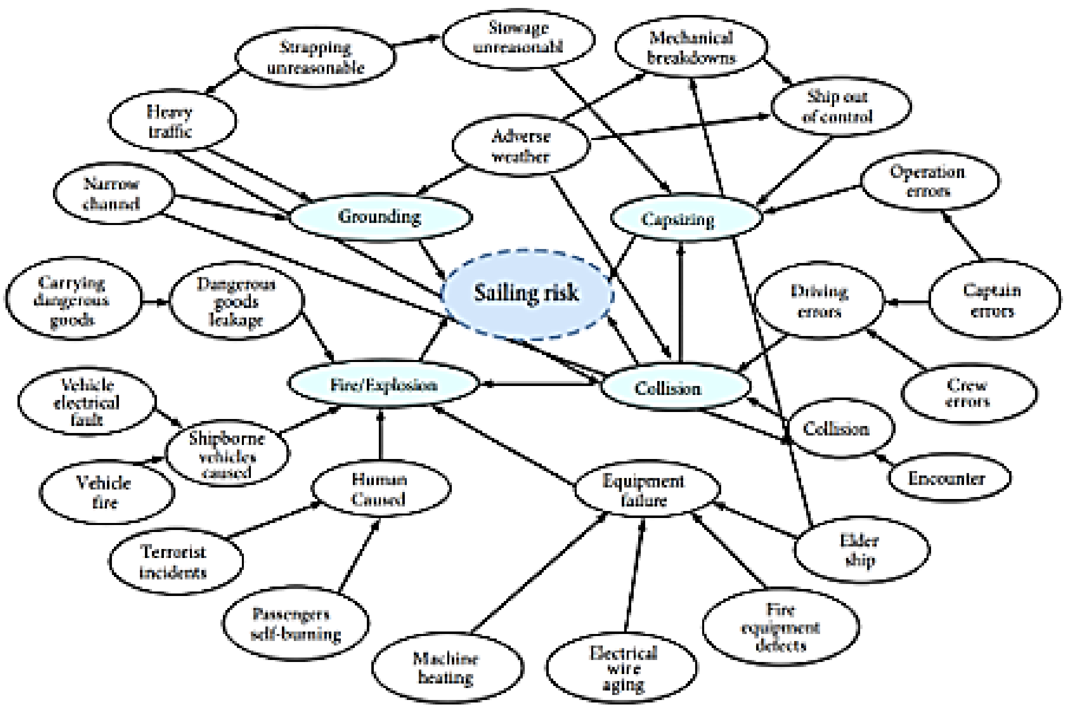

Figure 4. Graphical network of BN for RoPax sailing risk analysis (Zeng, Yang and Zhang, 2014)

Dynamic Modelling: The most effective modelling techniques for dynamic risk modeling in manoeuvring will be selected. The model must provide real-time integration of diverse data (e.g., from AIS systems, weather sensors, and navigational data). The research will use FMBS (Full Mission Bridge Simulations) simulation models.

Risk Assessment and Prediction: Optimal methods will be chosen for assessing and forecasting risks during manoeuvring operations in dynamically changing conditions. Risk forecasts' accuracy will be evaluated compared to traditional static methods. The effectiveness of various risk assessment and forecasting methods will be examined in the context of dynamic modelling. The accuracy of risk forecasts obtained from the dynamic model with traditional static methods will be compared. The modelling results will improve decision-making and operational processes during manoeuvring.

Model Validation: Methods for validating the dynamic risk model will be based on simulation studies and real-world scenarios. Limitations and challenges related to implementing the model in actual operational conditions will be addressed. Model tests will be conducted on manoeuvring simulators to verify their accuracy and reliability. The results of simulations will be compared with data from actual manoeuvres of RO-PAX vessels to assess the model's effectiveness in actual conditions. The model will be verified based on qualitative and quantitative indicators.

Practical Application of Results: The research findings may provide tools that operators of RO-PAX vessels, shipping companies, pilot stations, port authorities, and maritime administrations can directly apply. The developed dynamic risk model can serve as a basis for:

- Improving operational safety standards.
- Increasing risk awareness among crews and operators.
- Streamlining training and decision-making processes.
- Implementing new technologies and procedures in risk management.

The main research problem is developing a dynamic risk model (DRA) considering changing operational conditions. This model should address the following questions:

1. What technical factors influence the risk of manoeuvring RO-PAX vessels?
2. How do hydrodynamic conditions, such as sea currents and wind, affect navigational safety?
3. How can the crew's experience and skills alter the risk level in various operational scenarios?

4.1. Research of Methods and Models

Expert Data Analysis: Utilising expert knowledge to identify potential navigational hazards. Building a preliminary general model.

Dynamic Risk Analysis (DRA): Applying advanced methods of dynamic risk analysis that consider variable operational conditions and the duration of events. DRA will allow for a more precise real-time risk assessment, crucial for effective maritime safety management.

Machine Learning (ML) Techniques: Utilising machine learning techniques to analyse large datasets (Big Data) related to the maritime operations of RO-PAX vessels. ML will enable the identification of patterns and risk prediction based on various factors affecting navigational safety.

4.2. Implementation of Machine Learning

Rapid progress and multiple machine learning (ML) uses have recently captured widespread attention. Machine learning provides systems with the ability to learn tasks without explicit programming, and this capability increases both its attractiveness and performance. ML algorithms independently learn from data and use inductive reasoning to produce predictions about previously unseen inputs not included in the training data. Machine learning enables practical and economical solutions for complex tasks where traditional systems incur excessive costs. Machine learning development advancements and potential uses consistently capture significant interest from various industries and disciplines (Borjalilu 2024).

5. BIG DATA ROLE IN RISK MODELLING

5.1. The Role of Big Data in Risk Assessment

Enhanced Risk Identification: Big Data Analytics helps businesses evaluate extensive risk areas by analysing multiple data channels. Organisations analyse internal transaction records alongside customer behavior insights, social media activity data, sensor information, and external market data for risk identification. Advanced analytical methods, such as anomaly detection and sentiment analysis, enable organizations to detect early warning signs of potential risks and vulnerabilities, leading to timely preventive measures. („The Application of Big Data and AI in Risk Control Models: Safeguarding User Security” 2024)

Improved Risk Prediction: By analysing historical data patterns, organisations can enhance risk prediction accuracy using Big Data Analytics. Organisations that utilise predictive modelling, alongside machine learning techniques, can predict future risk situations and determine their probability and potential consequences in order to prioritise appropriate risk mitigation actions. Organisations gain the ability to tackle potential threats and vulnerabilities through this proactive approach before they develop into more serious problems. („The Application of Big Data and AI in Risk Control Models: Safeguarding User Security” 2024)

Real-time Risk Monitoring: Big Data Analytics enables organisations to continuously monitor key risk indicators and occurrences by analysing streaming data and sensor inputs. This capability allows organisations to quickly detect new risks and opportunities and minimise the response time following risk emergence. Organisations can obtain critical insights about their risk exposure through data visualisation dashboards and automated alert systems, enabling them to implement fast corrective measures to prevent losses and disruptions.(„The Application of Big Data and AI in Risk Control Models: Safeguarding User Security” 2024)

5.2. Integration of Big Data and AI in Risk Control.

Several recent research reports have deeply studied the synergies between big data analytics and AI. One of the key findings from the research in this field are („The Application of Big Data and AI in Risk Control Models: Safeguarding User Security” 2024):

1. Organisations can significantly enhance risk control systems by integrating Big Data analytics and Artificial Intelligence (AI). Through the interaction of these domains, organisations can extract actionable information from large data sets, which leads to the development of proactive risk mitigation strategies.
2. Data Fusion and Analysis: Using AI algorithms and Big Data analytics permits the combination of structured and unstructured data collected from multiple sources, such as social media platforms, IoT devices, and financial transaction records. We can perform comprehensive risk assessments through synthesis analysis because hidden patterns and correlations that evade traditional methods become visible.
3. Predictive Modelling and Forecasting: AI-driven predictive modelling uses past data to forecast future risks more precisely. Through machine learning tools like neural networks and decision trees, organisations can recognise developing risk patterns and predict future threats, enabling them to deploy preventive risk management tactics.
4. Real-time Monitoring and Detection: AI-based anomaly detection algorithms, combined with Big Data streams, enable the real-time analysis of risk indicators. By constantly examining data streams for unexpected changes, organisations can rapidly recognise emerging risks and take steps to reduce their effects.

Combining this with issues with the ones directly related to the scope of the study, we must also include the following:

5. Advanced Computing Technologies (Edge Computing, IoT): Establish Internet of Things (IoT) networks and Edge Computing systems to track and retrieve live data from RO-PAX vessels. Advanced data analysis technologies will be critical in risk management and decision-making during maritime operations.
6. Predictive Modelling: Developing predictive risk models for navigational safety requires considering various factors affecting RO-PAX vessel maneuvers' safe operation. These models serve as tools to simulate different situations, while evaluating the performance of suggested risk management strategies. The various methods target the development of a sophisticated risk management model that detects potential dangers and enables decision-makers to implement practical safety measures for next-generation RO-PAX vessels.

5.3. Dynamic fault tree (FT) models

The Fault Tree (FT) is a dependable deductive method for evaluating system reliability, maintenance performance, and safety, while analysing failure occurrences. This tool traces failures back to their source by connecting failure modes with logical gates and binary variables. The Fault Tree (FT) provides a graphical framework to analyse dependability and discover causes of failures that affect the Top Event (TE). The Top Event (TE) stands for a system failure, which creates the potential for a major accident to occur. During the construction of the FT, analysts trace causal relationships backwards from the TE to find potential failure points. Once the FT fully develops, the analysis phase will enable qualitative and quantitative evaluations. Through qualitative analysis, the research aims to discover the Minimal Cut Set (MCS) (Mamdikar, Kumar, & Singh 2022). Frank Bird's 1969 research originally presented the accident pyramid, which analysed 1,753,498 accidents from 297 cooperative companies. The reported incident numbers only represent a portion of the total events because many near-miss situations have not been documented.

5.4. Reliability Centred Maintenance

Reliability Centred Maintenance (RCM) Analysis workflow. This workflow provides the basic, high-level steps for using this module. The steps and links in this workflow do not necessarily reference every possible procedure. The procedure can be presented as follows:

1. Create the RCM Analysis record.
2. Create the Analysis team.
3. Define the equipment and location list, which helps define the RCM system. Note that each RCM FMEA Asset record can optionally be linked to an Equipment or Functional Location record.
4. Define the system's functions.
5. Define functional failures for each system function.
6. Define failure modes for each Functional Failure.
7. Define the failure effects for each Failure Mode.
8. Define Recommended Actions for each Failure effect

5.5. Results

The new multi-layered risk prediction model produces more accurate forecasts than conventional static methods. Data analysis from real-life RO-PAX vessel manoeuvres reveals essential safety-related factors, i.e.:

1. Operating at high speeds raises the chances of vessel collisions and additional safety incidents. Research indicates that vessels should modify their optimal manoeuvring speed according to waterway conditions.
2. Strong winds and limited visibility create significant challenges for vessel manoeuvrability. Machine Learning algorithms enable accurate predictions of weather condition changes and their impact on safety.
3. Vessels with more experienced crews tend to make superior decisions during emergencies. Research demonstrates that simulation exercises and training sessions produce marked improvements in crew abilities.

The model evaluated interactions with other vessels as vital for operations in ports and narrow straits. The Automatic Identification System (AIS) data enables studies of shipping traffic patterns to locate possible navigational risks. According to the results, dynamic risk assessment methods notably improve navigational safety during challenging conditions. The model has proved that combining data sources, such as AIS and weather sensors, leads to better prediction accuracy.

6. DISCUSSION

The primary difficulty faced during maritime risk assessment stems from inadequate standardised evaluation methods. The diversity of risk assessment methods as used by different organisations and agencies creates confusion when interpreting results. It is essential to create standardised metrics that allow for consistent comparison of results across different situations. The combination of Big Data and AI technology holds great promise for advanced risk control methods, but faces multiple hurdles that must be addressed to implement these solutions effectively. The effectiveness of Big Data analytics and AI algorithms suffers when data quality is poor and standardised governance frameworks are absent. Effective risk management depends on reliable insights extracted from data that maintain accuracy and integrity, while complying with regulatory standards. The 2024 study "The Application of Big Data and AI in Risk Control Models: Safeguarding User Security" explores these concepts. Technical challenges arise when combining multiple data sources with AI technologies because of problems related to data compatibility between systems and the need for scalable solutions. Businesses must allocate resources towards strong integration structures and data systems for smooth integration workflows. 2024 discovers how Big Data and AI protect user security through risk control models. Using AI within risk control systems creates ethical challenges in protecting data privacy, ensuring unbiased results, and maintaining algorithmic transparency. Organisations must implement ethical AI frameworks, while adhering to regulatory standards in order to prevent data misuse and discriminatory outcomes. (Kuzlu, Fair, & Guler 2021). The implementation of IoT and Big Data technologies transforms risk assessment methodologies. Ongoing surveillance of operational conditions helps organisations respond more rapidly to evolving situations. The decision-making process benefits from these technologies since they deliver real-time data that organisations can utilise for risk assessment.

7. CONCLUSIONS

The proposed dynamic risk model is an innovative tool that can be practically applied by shipowners, maritime administrations, and organisations focused on maritime safety. Its implementation will contribute towards better risk management, crucial in increasing maritime transport volume. Future research should focus on further development of predictive models and integration of various data analysis techniques. Long-term studies assessing the effectiveness of implemented models in operational practice are also recommended. ML, IoT, Big Data, and AI must create a dynamic risk model to challenge the problems by integrating each technology. Finding and developing a final method as a basis for a dynamic risk assessment model is essential for future research.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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