Reliability Engineering and System Safety 270 (2026) 112188

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Impact of voyage segments on maritime accidents: An analysis of navigational factors and accident causes

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ARTICLE INFO

Keywords:
Maritime accidents
Voyage segments
Bayesian networks
Scenario analysis
Risk assessment

ABSTRACT

Maritime transportation, a cornerstone of global trade, faces significant risks from maritime accidents, which can result in severe human casualties, substantial property loss, and extensive environmental damage. This study aims to improve the understanding of how different voyage segments, coastal waters, open seas, and restricted waters, influence maritime accidents by systematically analysing navigational characteristics and Risk Influential Factors (RIFs) across segments. The study employs a Tree-Augmented Naïve Bayes (TAN) model to quantify the probabilistic influence of RIFs on accident occurrence, enabling the explicit modelling of interdependencies that traditional approaches fail to capture. Scenario analysis is further conducted to assess segment-specific accident patterns and to identify how operational, environmental, and human-centred factors vary across navigational contexts. The results reveal both shared and segment-unique root causes, as well as high-risk transition zones where accident likelihood changes markedly between segments. By integrating voyage-segment analysis with a TAN structure, this paper advances maritime accident modelling beyond prior applications and provides actionable insights for risk-informed decision-making. The findings support the optimisation of route planning, the design of segment-specific and transition-focused safety measures, and the development of more effective maritime safety management strategies across diverse operational environments.

1. Introduction

Maritime transportation, one of the major modes of transport [1], plays a crucial role in global trade by handling over 80 % of international freight [2]. Its characteristics include cost-effectiveness, low freight charges, and high cargo capacity [3]. However, it also faces significant risks from various maritime accidents, which can lead to injuries, fatalities, and a loss of confidence in the industry. These accidents result in substantial property damage, including the loss of ships and cargo, and have long-term economic effects [4]. Additionally, accidents can cause severe environmental pollution, such as oil spills and chemical leaks [5], threatening maritime ecosystems and human health [6]. Therefore, while maritime transportation is essential for global trade, addressing the risks associated with accidents is vital for enhancing navigation safety and protecting lives, property, and the environment.

The maritime navigation process consists of three stages: pre-navigation, during navigation, and post-navigation, each crucial for ensuring safety. The 'pre-navigation' stage involves planning, vessel inspection, and crew preparation, while the 'during-navigation' stage focuses on monitoring environmental conditions, preventing collisions, and maintaining emergency readiness. The 'post-navigation' stage includes vessel inspections, accident reviews, and record maintenance. Strict adherence to safety standards and procedures across these stages is essential for safe maritime navigation. Among these, the voyage segment is particularly critical, referring to a specific leg of the journey from departure to destination. During different voyage segments, vessels encounter complex weather, maritime traffic, and navigational hazards. Research on voyage segments helps prevent maritime accidents, optimises route planning, and enhances vessel safety by predicting potential

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https://doi.org/10.1016/j.ress.2026.112188
Received 13 August 2025; Received in revised form 1 December 2025; Accepted 2 January 2026
Available online 2 January 2026

risks and informing effective preventive measures [7]. Additionally, understanding the characteristics of different voyage segments can improve navigation safety and reduce costs. A thorough analysis of voyage segments is vital to enhancing maritime navigation safety and preventing accidents. However, previous studies in the field have failed to address maritime accidents across different segments in a comprehensive and comparable manner. As a result, the root causes of risks specific to each segment are not only insufficiently analysed and understood, but the lessons learned across segments are also not effectively cross-referenced. This limits the potential for cross-fertilisation of effective risk control measures, both within individual segments and in transition areas involving multiple segments.

Previous studies have explored various aspects of global maritime accidents, such as spatial patterns, environmental risks, and accident cause analysis. For instance, Y. Zhang et al. [8] employed Kernel Density Estimation (KDE) and Spatial Density Analysis, and Zhou et al. [9] used geospatial techniques with K-means clustering and Extreme Gradient Boosting. However, their studies, which focus on macro-level spatial distribution, overlook the complex conditions and unique risks associated with specific voyage segments. Lan et al. [10] utilised an association rule learning algorithm to identify correlations among factors in a maritime accidents database, and Teixeira and Guedes Soares [11] applied Bayesian Networks (BN) for similar purposes. Although these methods provide valuable insights, Chen and Wang's approach may lack attention to specific geographic details, while the BN analysis often emphasises vessel location and movement over operational and environmental factors unique to segments. Li et al. [12] used the Multiscale Geographically Weighted Regression (MGWR) model to examine spatial heterogeneity in accident factors. However, this method may miss small-scale or localised risks relevant to specific maritime segments.

Similarly, Huang et al. [13] employed GIS for hotspot identification and spatial analysis, but their research focuses on accident locations rather than delving into the specific causes along particular routes or high-traffic areas. Wang et al. [14] analysed the spatial patterns of global maritime accidents using density and clustering techniques. However, these studies may not fully capture the complexity of accident causes or specific risks tied to voyage segments, focusing more on accident clustering than on effective risk management within those segments. Although Chou et al. [15] examined environmental factors such as wind, waves, tides, and currents using regression methods, their study may not consider crucial factors such as operational procedures, traffic density, and crew behaviour, which are critical factors in specific voyage segments. Zhang et al. [16] primarily focused on collision risks, potentially overlooking other threats like grounding, fires, or mechanical failures, which can vary significantly in different regions, such as the Jiangsu section of the Yangtze River, due to local geographic and traffic conditions. Similarly, Özbaş et al. [17] employed probabilistic risk models in simulations to establish baseline risks at the two entrances of a strait. However, by concentrating only on these locations, their study may not provide a comprehensive risk assessment for the entire voyage segment or regions with similar conditions, limiting the broader applicability of their findings.

Although showing some attractiveness, existing literature focuses on individual segments or mixes all segments together for a systematic maritime analysis without the different segments as a distinguished influential factor for accident investigation and prevention. Further, most existing methods emphasise macro-level spatial distribution, neglecting the complex navigation conditions and unique risk factors within individual segments. The lack of in-depth analysis in these studies results in an incomplete understanding of segment-specific environmental and operational conditions. A detailed investigation into specific voyage segments is urgently needed, focusing on environmental characteristics, navigation frequency, and vessel diversity. Such an analysis is essential to enhance the precision and effectiveness of maritime safety management, addressing the unique risks and conditions inherent to different voyage segments. It is particularly important given the facts that 1) recent serious maritime accidents (e.g., the Suez canal blockage in 2022 and Baltimore bridge collision in 2024) are exposing significant segment-related characteristics, and 2) increasingly new shipping corridors are being proposed and developed, involving a full set of different segments in a systematic way in which an increased number of overlaps covering multiple segments as the transitions. The significance and timeliness of this study are therefore justified by its ability to reveal the root causes of risk and their interactions for cross-referencing, therefore addressing transitional areas that have been overlooked in the existing literature for the first time.

This study aims to explore the impact of different voyage segments on maritime accidents using a TAN model. In theory, a detailed analysis of these segments can help uncover the specific mechanisms through which they influence accident risks, providing valuable insights not only for the shipping sector (e.g., corridors) but also for related sectors such as maritime logistics and supply chains. By analysing the role of voyage segments in accident occurrence, this research enhances our understanding of how segment-specific characteristics affect navigational behaviour and overall maritime safety. The findings support improvements in several key areas: optimising the design and management of voyage segments, enhancing navigational aids and vessel identification systems, and strengthening coordination between individual segments and broader maritime safety strategies to improve both traffic efficiency and risk mitigation. The study adopts a systematic approach, analysing voyage segments across coastal waters, open seas, and restricted areas. It evaluates the influence of vessel conditions, crew competencies, hydrometeorological factors, and operational management practices on the safety of specific segments.

The relationship between voyage segments and common types of maritime accidents, such as collisions, groundings, and oil spills, is thoroughly assessed. By deepening our understanding of the safety implications of segment-level navigation, the paper offers practical, evidence-based guidance for maritime authorities, ship operators, and other stakeholders, contributing to safer and more efficient vessel operations. The contributions of this paper include:

(1) Systematic analysis of voyage segments.

This paper conducts a rigorous and integrative evaluation of three distinct voyage segments, coastal waters, open seas, and restricted waters, examining their traffic density, environmental conditions, navigational complexity, and operational challenges. By analysing these segments collectively rather than in isolation, the study reveals their interrelationships and combined impact on maritime accidents, addressing the gap in understanding how segment-specific characteristics shape overall maritime risk. This provides a robust foundation for informed, risk-based decision-making in maritime navigation.

(2) Linking voyage segments to maritime accident types.

This paper establishes a clear, data-driven connection between voyage segments and specific accident types, including collisions, groundings, and equipment failures. By demonstrating how each segment uniquely influences safety outcomes, the study identifies segment-specific vulnerabilities and critical risk factors, highlighting where targeted interventions can most effectively reduce accident likelihood and improve operational safety.

(3) Guidance for enhanced voyage segment management.

Based on cross-segment analysis, the paper delivers actionable recommendations for optimising voyage segment management. It proposes integrated strategies for cross-segment risk mitigation, dynamic route planning, and proactive safety management, moving beyond traditional approaches that focus on isolated segments. These insights directly support stakeholders in enhancing maritime safety, operational efficiency, and resilience across the full spectrum of voyage environments.

The rest of this paper is organised as follows: Section 2 reviews the literature, summarising the current state of maritime accident analysis and identifying research gaps. Section 3 describes the established TAN model, including model construction and sensitivity analysis. Section 3 also presents model validation, focusing on accuracy, predictive performance, and consistency. Section 4 applies scenario simulations to evaluate maritime accident risks in specific voyage segments, focusing on the practical implications of the key findings. The results are discussed in terms of how they can inform better safety practices and operational decisions. Finally, Section 5 summarises the results, outlines the practical implications for maritime risk management, and offers recommendations for future research to further enhance maritime safety.

2. Literature review

The following section is structured into three parts to provide a foundation for this paper. Section 2.1 presents a comparison of existing maritime accident risk analysis models, followed by Section 2.2, which focuses on the application of BN to maritime accident analysis across different voyage segments. Section 2.3 identifies the key research gaps addressed in this work.

2.1. Comparison of maritime accident risk analysis models

The analysis of maritime accidents has undergone substantial development, with a wide range of methodological approaches being proposed to predict accident occurrence and identify contributory risk factors. These approaches include traditional statistical models, machine-learning classifiers, and various probabilistic frameworks. A critical review of this literature highlights ongoing methodological tensions, particularly between conventional frequency-severity models and emerging systems-oriented and resilience-based approaches that aim to capture cross-scale interactions and dynamic system behaviour.

Multi-model approaches have been introduced to leverage the complementary strengths of different techniques while mitigating their individual limitations. For example, recent studies have combined gradient-boosting algorithms such as XGBoost with SHAP-based interpretability [18], or integrated Decision Trees (DT) with BN to enhance diagnostic capability [19]. While such hybrid methods have demonstrated promising performance, they typically require large, high-quality datasets and introduce additional computational and modelling complexity. These factors may limit their operational applicability in safety-critical maritime contexts where data are often sparse, heterogeneous, or inconsistently reported. Furthermore, although BNs are widely used in maritime safety research due to their transparency, interpretability, and ability to represent conditional dependencies, their integration with broader systems-theoretic methodologies, such as system dynamics modelling or agent-based modelling, remains limited. XGBoost, a decision tree-based algorithm combined with SHAP, enhances prediction accuracy and improves the model's interpretability, making it well-suited for handling high-dimensional data. However, this method requires large datasets and has limitations when considering human factors. Combining DT and BN offers a better explanation of complex causal relationships and applies to various types of maritime accident analysis. Methods like TOPSIS and Multiple Correspondence Analysis (MCA) [20], when combined, allow for the consideration of multiple dimensions, such as human, environmental, and management factors, thereby compensating for the shortcomings of single-model methods that may neglect certain factors. However, multi-model methods are complex in structure, computationally expensive, and highly dependent on data completeness and quality.

Recent studies, such as Zhang et al. [4], which explores the economic implications of the Northern Sea Route, and Feng et al. [5], which addresses maritime accidents involving chemicals, offer important insights into the evolving landscape of maritime safety. However, these studies primarily focus on specific risks or geographical contexts, underscoring the need for more integrated approaches that link disparate risk factors across different voyage segments. While these works contribute valuable perspectives on specific risks, such as the economic impact of new shipping routes or the challenges posed by chemical maritime accidents, they do not fully integrate the broader, systemic understanding required to address the full spectrum of maritime accident risks across diverse voyage segments.

Statistical models, including various forms of regression analysis, have long been used to analyse maritime accident data and examine potential causal relationships. While these approaches offer a structured means of quantifying the effects of individual predictors, they are inherently limited in their ability to represent the dynamic, nonlinear, and multi-faceted nature of maritime risk. Frequency-severity models, for instance, rely on simplified quantitative relationships and often assume linearity or independence among covariates, thereby overlooking the complex interactions that characterise real-world maritime operations. Similarly, ordinal logistic regression [21] and count models such as negative binomial and Poisson regressions [22] can identify statistically significant predictors of accident severity or frequency, but they exhibit several critical shortcomings. First, these models struggle to capture interdependencies among multiple risk factors, despite the fact that human, technical, environmental, and organisational elements interact in tightly coupled ways across different voyage segments. Second, they typically do not incorporate temporal or contextual variability, such as evolving weather conditions, traffic density, or operational decision-making, all of which can substantially modify accident likelihood. Third, human and socio-technical factors, which play a central role in maritime accident causation, are often excluded or treated as static covariates, limiting the ability of these models to represent emergent or adaptive behaviours. Finally, the rigid structure of traditional statistical models constrains their ability to support reverse inference, scenario analysis, and probabilistic reasoning, tools that are increasingly essential in modern risk assessment.

Probabilistic models, particularly BN, have gained increasing prominence in maritime safety research due to their capacity to represent complex conditional dependencies and to accommodate uncertainty, incomplete information, and heterogeneous data sources. Compared with traditional regression-based approaches, BNs offer clear advantages in terms of modelling flexibility, interpretability, and their ability to support scenario analysis and probabilistic inference. Their dynamic updating capability also enables comprehensive sensitivity analyses, making them valuable tools for predictive risk assessment. For example, BN-based models have been applied to assess safety risks along the 21st Century Maritime Silk Road [23], integrating multiple risk factors and enabling structured scenario-based evaluations. However, the limitations of probabilistic models are also evident: constructing these models requires large amounts of high-quality data, and the computational complexity can be high, leading to increased practical implementation costs.

The research presented in Table 1 further illustrates the performance of these three group methods (i.e., multimodal, statistical, and probabilistic) in practical applications. Multi-model methods have shown notable improvements in prediction accuracy and interpretability, particularly in studies conducted in the Zhejiang waters [18], where the combination of XGBoost and SHAP enhanced the model's effectiveness. Nevertheless, these methods are still constrained by data quality and sample size, and the lack of attention to human factors remains a significant issue. Statistical models, such as Ordinal Logistic Regression and Negative Binomial Regression [21,22], are typically used to handle more straightforward datasets and have revealed relationships between accident severity and influencing factors. While these models are straightforward, they lack the comprehensive handling of complex multi-factor interactions. Probabilistic models, especially BN [23], are widely applied in maritime accident risk assessments and have proven effective in handling complex causal relationships, making them suitable for multi-factor analysis. However, their reliance on high-quality data and

Table 1
The related studies based on three different kinds of methods.

Method Type	References	Methods	Advantages	Disadvantages	Datasets	Research content
Multi-Model Methods	[18]	XGBoost and SHAP	(1) Improve the interpretation (2) Accuracy of forecasts	(1) Limited data samples (2) Lack of theoretical support (3) Exclusion of human factor	Zhejiang seas: 105 maritime accident records from the past 10 years	Develop a maritime accident prediction model to analyse factors affecting navigation safety.
	[20]	TOPSIS, BN, MCA, HC and CT	(1) Consider human factors (2) Combine methods to overcome limitations	(1) Data Completeness (2) Accuracy Limitations	Global waters: Involving 161 reports from 208 vessels from 2012 to 2017	Detect and explain contributing factor patterns of maritime accident types.
	[24]	FTA and BN	Dynamic risk assessment	Data limitations	European Waters: 114 grounding reports from 2000 to 2020	Analyse and assess grounding accident risks.
	[25]	BN and GIS	A couple of Perl external function interfaces and GIS software	(1) Data quality (2) Reliability limitations	Gulf of Finland: 1080 simulations modelling oil spill spread	Environmental risk assessment and visualisation.
	[26]	TAN-BN and Machine Learning	(1) Uncover a hidden pattern (2) Explain the influencing factors from multiple perspectives	(1) Subjective model (2) Independent data (3) Limiting practical application	Global waters: Involving 1294 ships from 2000 to 2019	Classify maritime accident severity to identify key influencing factors and mechanisms.
	[19]	DT and BN	Identify factors influencing oil spill severity in ship accidents	(1) Incomplete datasets (2) Limited accuracy	Global waters: 1468 ship accidents resulting in oil spills from 2002 to 2015	Key factors affecting oil spill severity in ship accidents were analysed.
	[27]	Regression models	Improve credibility and accuracy	(1) Lacks traffic information (2) Key factors omitted	Global waters: 24,301 ship accidents recorded in 33 waters from 2001 to 2011	Develop models to analyse factors affecting injury severity and mortality in ship accidents.
	[22]	Negative Binomial and Poisson Regression	(1) Enhance data credibility (2) Verify robustness	Limitations of the dataset	US Coast Guard: 912 passenger vessel accidents from 1991 to 2001	Analyse factors affecting injuries, fatalities, disappearances, and damage costs in passenger ship accidents.
	[28]	BN, Regression model and Expert Judgment	Improve the accuracy, reliability, and robustness of the model	(1) Subjective Expert judgment (2) Data limitations	Conditional probabilities: Filled based on expert judgment	Assess risks of dangerous goods ships moored at ports and analyse the impact of human and environmental factors on hazardous goods accidents.
	[29]	BN, Statistics and Expert Knowledge	(1) Capture complex dependencies and enhance accuracy (2) Credibility by combining data and expert knowledge	Prediction error	Tianjin harbour: 234 accident records from 2008 to 2013	Analyse dependencies between indicators and accident consequences and predict their probability distribution.
	[30]	FSA, BN and Risk Matrix	Use structured methods like FSA and BN to assess Yangtze River navigation risks	Data limitations High demand for data and expertise	Yangtze River: 455 accidents in 2009	(1) Evaluate navigation risks. (2) Analyse the impact of parameters on accident outcomes.
	[31]	N-K	Intuitively show correlations between influencing factors	(1) Regional and sample limitations (2) Difficulty in modelling complex systems	Chinese Sea: 922 accidents from 2000 to 2020	Analyse the interaction of human, environment, and management factors in maritime accidents.
	[32]	N-K	Reveal complex interactions among risk factors and identify high-risk coupling scenarios	(1) Limited by small sample size (2) Lack of probabilistic risk quantification.	40 maritime accident investigation reports in ice-covered waters.	Analyse the coupling effects of risk factors and causation pathways.
	[33]	FAHP	Incorporate multiple stakeholders' opinions and weights in risk perception assessment	Survey results are subjective and biased	Istanbul Strait: 232 accident records from 2000 to 2011	(1) Assess stakeholders' risk perception in the Istanbul Strait. (2) Analyse the discrepancy with actual maritime accident data.
	[34]	OPA and GRA	Combine subjective and objective weighting for balanced risk assessment	(1) Rely on historical accident data (2) Subjective judgements in OPA may introduce bias	Maritime accident statistics in Korean waters from 2018 to 2022	Rank eight types of accidents by risk level, identifying safety-related accidents and collisions as the highest-risk categories.
	[35]	Kernel density, Hotspot analysis and Maxent modelling	Identify statistically significant accident hotspots, reveal the most influential spatial factor and provide intuitive risk visualisation	(1) Data limitations (2) Static analysis doesn't capture temporal risk variations	Philippine Coast Guard records and International Maritime Organization (IMO) Global Integrated Shipping Information System (GISIS) database	Map high-risk zones near population centres to guide safety interventions.
	[36]	CRITIC, WRSR, DBSCAN, siting	Cut response times, tracks accident hotspots and severity, and is scalable for waterways	(1) Assume static accident patterns (2) Require high-	Yangtze River accident records from 2019 to 2021	Recommend over three emergency bases for the Nanjing section to achieve

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Table 1 (*continued*)

Method Type	References	Methods	Advantages	Disadvantages	Datasets	Research content
		optimisation model		quality positional accident data		multi-coverage of high-risk zones.
	[37]	NVivo text mining, risk control framework	Bridge the gap between theoretical and operational risk management	(1) The qualitative approach limits quantitative risk assessment (2) Potential bias from report availability/ quality	Global MAIRs for Arctic/ice-covered waters	Propose targeted RCOs for ship-ice collisions and other Arctic hazards and highlight human-organisational factors in polar operations.
	[38]	AutoML, SHAP	Automate the model selection process and identify high-risk operational scenarios	(1) Black-box nature limits interpretability (2) Require large, clean training datasets	40 years of Norwegian maritime accident records	LightGBM outperforms other classifiers and provides real-time risk assessment framework.
	[39]	K-means and TOPSIS	Quantify sparse Arctic infrastructure capabilities and integrate temporal and spatial rescue factors	(1) Simplify complex polar environmental conditions (2) Limited by historical accident data scarcity	Historical Arctic accident locations and port infrastructure databases	Rank emergency ports by ERT and PEC metrics and recommend optimal SAR resource allocation.
Statistical Models	[40]	ARIMAX	Forecast results are more comprehensive	(1) Human factors not considered (2) Data set limitations (3) Poor prediction techniques	Global waters: Global maritime accident data from 2004 to 2019	Consider the impact of 8 factors on maritime accidents.
	[21]	Ordinal Logistic Regression	Comprehensively understand factors influencing accident severity	(1) Under-reporting (2) Neglect of human factors (3) Limited focus on management enablers.	Global waters: 1207 accidents from 2010 to 2019	Explore the relationship between maritime accident severity and influencing factors.
	[41]	ZIOP	Explore factors affecting two injury severity states	(1) Incomplete dataset (2) Insufficient model flexibility	Global waters: 1128 maritime accidents	Discuss and analyse factors affecting maritime accident injury severity.
	[42]	Ordered Probit	More accurate assessment of affecting factors	(1) Data limitations (2) Interactions between factors not considered	The Northeastern US: Fishing vessel accidents from 2001 to 2008	Assess the determinants of vessel damage and crew injury severity.
	[43]	Regression model	Use objective and reliable historical accident data for analysis	(1) Limitations of historical data (2) Incomplete consideration of all factors	Hong Kong Waters: 2012 maritime accidents data	Explore the regularity and key factors of Stock Connect risks.
	[44]	Statistical analysis	(1) Standardise classification improves comparability (2) Highlight high-risk areas	(1) Underreporting may skew results (2) Lack of predictive or probabilistic modelling.	156 accidents along the North-East Passage from 2000 to 2020	Profile accident trends and advocate for stricter Polar Code enforcement.
	[45]	Multilateral comparative analysis	Multilateral accident analysis across four time periods, integrating two datasets	(1) Limited by potential reporting inconsistencies across jurisdictions (2) Doesn't account for fleet composition changes over time	Korea Maritime Safety Tribunal, IMO, and EMSA	Reveal stagnation in Korean fleet safety despite ISM Code implementation.
Probabilistic Models	[23]	BN	(1) Effectively identify and analyse safety risks (2) Consider multiple factors	(1) Limited scope and quality (2) Low external validity	21st Century Maritime Silk Road (MSR): 413 reports from the IMO from 2010 to 2017	Analyse maritime transport safety risks of MSR and conduct scenario analysis on navigation risks.
	[46]	NBN	(1) Accurate consequence estimations (2) Reliable basis for emergency management	Subjectivity and uncertainty in model establishment and parameter setting	Yangtze River: Historical data on collision accidents in the lower reaches	Model the consequences of the collision, considering the causal factors.
	[47]	BN	A proactive framework for updates and sensitivity analysis	(1) Accuracy requires verification (2) Data limitations (3) Model complexity impacting outcomes	Gulf of Finland: Data on RoPax vessels in European waters based on risk	A systematic risk analysis framework focusing on collision risk in maritime transport systems.
	[48]	BN	Accident data risk analysis for reliable predictions	(1) Data limitations (2) Model building and parameter selection	Yangtze River: 663 accident records	Determine critical safety factors of congestion and predict congestion risk.
	[49]	BN	(1) Handle uncertainty in risk factors and data (2) Provide spatiotemporal risk analysis	(1) Complex model setup requires expert input (2) Limited by data availability for rare events.	Collision accident records and expert judgements from China's coastal ports	Assess collision risks, highlighting environmental and operational factors as key contributors.

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Table 1 (*continued*)

Method Type	References	Methods	Advantages	Disadvantages	Datasets	Research content
	[50]	BN	Enable real-time severity prediction, filling a critical data gap in bulk carrier safety	(1) Labour-intensive data collection process (2) Require regular updating with new cases	Over 120 ATSB maritime accident reports from 2000 to 2022	Identify accident type and emergency handling as top severity determinants for bulk carriers

the high computational cost are vital limitations in their practical applications.

In summary, each method has strengths and is suited to different research needs and data characteristics. New research is needed to explore how to effectively combine these methods to maximise their advantages, thus improving maritime accident risk prediction accuracy and practicality. In particular, combining multi-model and probabilistic approaches may yield better results in cases with complex data or interrelated factors, while statistical models remain an efficient choice when data is abundant, and the factors involved are relatively simple. Table 1 summarises the statistical models and multi-model methods used in different studies and lists in detail the application background, advantages and disadvantages of each method, the data sets used, and the specific content of the study.

A search for 'Maritime Accidents' on the Web of Science from 2000 to July 2025 yielded 3547 relevant journal articles. These articles were manually screened to identify those that discussed the elements of 'Geographical Location', 'Maritime Waters', and 'Voyage Segment'. As a result, 33 studies directly related to Voyage Segments were selected for in-depth analysis.

These studies were compared based on their methodologies, advantages, limitations, datasets, focus areas, and study regions, as summarised in Table 1. Of the selected articles, seven focus on global maritime waters [19–21,26,27,40,41], while 26 examine specific regional waters [18,22–25,28–39,42–50]. The predominance of global studies can likely be attributed to the availability of comprehensive datasets, which allow for broader analysis incorporating local management and environmental factors.

Recent advances in maritime accident prediction and causal analysis have incorporated sophisticated methods such as machine learning models [18,19,26,38], Multi-criteria Decision Analysis [20,31,33,34], time series analysis [40], and hybrid models [25,31,49]. Some studies have enhanced their approach by combining various modelling techniques [19,22,24–30,32,36,51]. These methods have contributed to a better understanding of accident dynamics and the integration of empirical data, strengthening the reliability of the models. However, challenges persist, particularly in areas such as data quality, feature selection, and model robustness. Many studies remain heavily reliant on the availability and accuracy of historical data, which directly influences the predictive performance of the models.

Moreover, subjective factors and parameter settings can compromise the reliability of model outcomes. The complexity of some models, coupled with insufficient evaluation of their robustness and generalisability, limits their practical applicability. Moving forward, future research must prioritise enhancing data quality, conduct thorough model validation, and strive for greater objectivity in interpreting results. These improvements are essential for increasing the accuracy and credibility of maritime accident predictions and risk assessments.

Probability models feature prominently in maritime accident research, with 17 studies utilising probability models or their combinations for analysis [19,20,22–28,30,42,43,47–50]. Among these, 12 specifically employed the BN method or its variants [19,22,24–30], such as the TAN [26] and the Naïve Bayesian Network (NBN) [46]. This underscores the pivotal role of probability-based approaches in this field, with BN being particularly effective for analysing complex accident data. Consequently, this study adopts BN as the primary analytical tool for prediction and analysis.

BN offers distinct advantages over traditional and alternative models in maritime accident analysis. Conventional methods such as Ordinal Logistic Regression, Zero-Inflated Ordered Probit (ZIOP), and Binary Logistic Regression effectively identify key accident factors. However, they are constrained by their reliance on fixed linear relationships, limiting their ability to model real-world complexities. Similarly, machine learning models like XGBoost deliver high predictive accuracy but often lack transparency and struggle to perform effectively with small datasets. Time series models like ARIMAX excel at capturing dynamic temporal changes but frequently overlook human and contextual factors critical to maritime accidents. In contrast, BN is adept at handling multi-factor interactions, providing interpretable results, and offering flexibility in capturing the intricate relationships inherent in accident data.

BNs are widely used in maritime safety research due to their ability to represent conditional dependencies among multiple interacting factors. Their graphical structure supports transparent system-level reasoning and enables both predictive and diagnostic inference, making them useful for risk assessment, accident investigation, and scenario analysis. BNs can also be updated dynamically as new evidence becomes available, and their built-in sensitivity analysis helps identify influential variables, supporting targeted risk-mitigation decisions.

This study advances previous BN applications by adopting a TAN model. TAN model relaxes the strong independence assumptions of naïve Bayes, allowing each variable an additional parent and thus capturing important conditional dependencies present in real maritime operations. The tree-augmented structure maintains interpretability and computational efficiency while accommodating a broad set of vessel, operational, environmental, and voyage-specific risk factors. By integrating these multi-level inputs, the TAN model represents cross-segment socio-technical interactions that earlier BN studies largely overlooked, enabling a more realistic and operationally meaningful assessment of accident risk across voyage stages.

This study utilises a global maritime accident database, which draws on data from key sources, including the IMO GISIS and Lloyd's Register Foundation (LRF) databases, covering the period from 2017 to 2021. The database compiles information on maritime accidents, such as accident dates, locations, involved vessels, and brief cause descriptions, in accordance with the IMO's reporting standards. Additionally, it includes detailed accident investigation reports, offering deeper insights into vessel operations, environmental factors, the accident sequence, and root cause analyses. To address gaps in the available vessel data, the study incorporates normalised ship information from the LRF, filling in missing details such as ship type, age, and hull construction within the IMO GISIS dataset. By linking the data using the ship's Maritime Mobile Service Identity (MMSI) and IMO number, consistency and accuracy are ensured across both databases. The enriched dataset is then analysed using BN methods to assess and forecast maritime accident risks.

The BN approach is particularly practical in managing complex probabilistic relationships and delivering reliable predictive outcomes [52]. Research on global maritime waters is crucial for identifying overarching trends and common challenges, providing insights that support international collaboration and policy development [53]. The ability of BN to address uncertainty, manage missing data, and offer strong interpretability makes it a powerful tool for understanding the mechanisms and influencing factors of maritime accidents [51]. Combining these strengths, this study contributes to advancing risk assessment and management strategies in maritime transportation safety.

2.2. Application of Bayesian network to maritime accident analysis across different voyage segments

Maritime risk research frequently adopts a three-segment navigational framework comprising restricted waters, coastal waters, and open seas. This classification aligns broadly with international maritime practice, although no single authoritative global standard formally codifies these categories. Instead, they are commonly interpreted with reference to navigational constraints and hydrographic conditions, consistent with IMO routeing guidance and International Hydrographic Organization (IHO) charting conventions. While this segmentation offers a useful basis for examining how navigational environments influence accident patterns, prior studies often analyse each segment independently, providing limited understanding of the interdependencies and transitional dynamics that characterise real-world maritime operations.

Restricted waters, such as port approaches, narrow channels, and straits, are characterised by confined geometry, shallow depths, dense traffic, and strict regulatory oversight. Such areas, referenced in national Vessel Traffic Service (VTS) schemes and IMO traffic separation arrangements, are associated with elevated risk levels due to limited manoeuvring space, increased cognitive workload for bridge teams, and complex local environmental conditions. These characteristics make restricted waters a critical focus for maritime safety analysis, particularly with respect to collision, grounding, and close-quarters incidents. Examples encompass the narrow channels of the Yangtze River downstream, spanning from Nanjing to Shanghai [30,46,48]; highly regulated ports such as Tianjin Harbour [29]; the Istanbul Strait [33], known for its demanding navigation environment; and Hong Kong Waters [43]. Navigational challenges in these areas are typically influenced by factors such as shallow water depth, surrounding terrain, and dense vessel traffic.

Open seas correspond to deep-water, minimally constrained navigation environments, typically located within international waters as defined under the United Nations Convention on the Law of the Sea (UNCLOS). Although vessels experience greater operational freedom in these areas, they remain exposed to significant environmental and mechanical stresses, including heavy weather, long-period swells, and sustained engine loads. These factors can contribute to elevated risks associated with equipment failures, loss-of-control events, and adverse human–machine interactions, indicating that open-sea navigation is not inherently low-risk despite reduced traffic density and spatial constraints. Research examples include global waters [19,26,40,41], the 21st Century Maritime Silk Road [23], worldwide maritime transport [20], and diverse sea areas with varied environmental conditions across 33 major global waters [27]. Open seas often involve fewer regulatory constraints, though environmental and climatic factors still pose challenges.

Coastal waters, which represent the transitional zone between restricted areas and the open sea, are influenced by local bathymetry, tidal dynamics, variable meteorological conditions, and mixed traffic patterns. Although often delineated operationally by coastal-state jurisdictions (e.g., territorial sea limits), the navigational complexity of these areas varies considerably. Factors such as shifting sediments, dynamic currents, diverse vessel types, and interactions between commercial, fishing, and recreational traffic contribute to a heterogeneous risk environment that differs markedly from both restricted waters and the open sea. Examples include sections of the lower reaches of the Yangtze River [21], known for connecting inland waterways to open seas; the northeastern United States [42], where navigation is influenced by coastal terrain; European waters [24]; and the Gulf of Finland [25, 47].

The studies investigating different voyage segments are summarised in Table 2, where various research areas are compared. While these studies provide valuable insights, the current literature reveals a significant gap in comprehensive analyses that address the unique risks and challenges associated with each segment of a voyage. Most research either focuses on individual segments in isolation or offers generalised insights into global waters, often overlooking the interconnected nature of these maritime zones.

Table 2
Classification of maritime research areas by voyage segments.

Voyage segment category	Research areas	References
Restricted waters	Sea areas under the jurisdiction of Zhejiang Maritime Safety Administration	[18]
	Lower reaches of the Yangtze River (e.g., Nanjing to Shanghai)	[30,46,48]
	Tianjin Harbour	[29]
	Istanbul Strait	[33]
	Hong Kong Waters	[43]
	China's Coastal Port Waters	[49]
	Arctic Waters	[32,39,44]
	Gulf of Finland	[25,47]
	Specific sections of the Yangtze River	[21,36]
Open seas	Global Waters	[19,26,40, 41]
	21st Century MSR	[23]
	Worldwide maritime transport	[20]
	The waters off the coast of Australia	[50]
	The surrounding seas of South Korea	[45]
	33 major waters around the world, including different sea areas and maritime environmental conditions	[27]
	The United States and surrounding waters	[22]
Coastal waters	Fishing boat accidents in the northeastern United States	[42]
	The coast of the Philippine Islands	[35]
	The coast of Norway	[38]
	The coast of South Korea	[34]
	The coastal area of the Arctic region	[37]

To achieve a cohesive understanding of maritime risks, it is crucial to integrate findings across all voyage segments. Such an approach would illuminate the interactions between restricted waters, open seas, and coastal waters, enabling a systematic risk assessment that reflects the complexities of entire voyages. For instance, accidents in restricted waters could cascade into coastal or open seas, disrupting logistics and vessel traffic flow, thereby amplifying the overall impact.

A detailed study of voyage segments is necessary to uncover their distinct risks, preventive measures, and interdependencies. A more integrated analysis of these segments is essential for developing targeted and effective maritime safety strategies. Addressing this gap in the literature will enhance the understanding and prevention of maritime accidents, contributing to safer, more efficient, and resilient maritime operations.

2.3. Research gaps

Despite notable progress in maritime accident analysis, several critical gaps remain, particularly regarding how risks evolve and interact across different voyage segments. Existing studies typically focus on restricted waters, coastal waters, or the open sea in isolation, offering valuable but fragmented insights. This segmented perspective overlooks the fact that maritime operations constitute a continuous socio-technical process in which risks can propagate or transform as vessels transition between navigational environments. A more integrated approach is therefore essential for understanding system-wide accident mechanisms and designing effective risk mitigation strategies.

(1) Lack of integrated and cross-segment analysis
Most existing research examines individual voyage segments independently, resulting in partial assessments that fail to

capture the full complexity of maritime risk. Studies focusing exclusively on restricted waters or open seas provide only localised insights and cannot identify cross-segment patterns or cumulative risk effects. Moreover, transitions between segments, such as movements from coastal waters into confined approaches, are often high-risk phases due to shifting navigational constraints, varying traffic density, and abrupt changes in operational workload. The absence of system-wide analyses limits the ability to model these transitional dynamics and to formulate comprehensive safety strategies. Addressing this gap requires analytical frameworks capable of incorporating all three segments and their interactions within a unified risk perspective.

(2) Limited linkage between accident causes and voyage segments

Although previous work has catalogued the causes of maritime accidents, few studies explicitly link these causes to the navigational characteristics of specific voyage segments. This disconnect impedes the development of targeted and context-specific safety interventions. Accident types such as collisions, groundings, mechanical failures, or pollution events may manifest differently depending on whether a vessel is operating in restricted, coastal, or open-sea environments. Without segment-level attribution, safety management remains overly generic and insufficiently responsive to the operational realities of each navigational context. This study addresses this limitation by explicitly mapping causal factors to voyage segments, enabling more precise and strategically aligned mitigation measures.

(3) Insufficient examination of interdependencies among risk factors

Many studies analyse environmental, operational, human, and vessel-related factors in isolation, overlooking the interdependencies that shape accident risks, especially during transitions between voyage segments. In practice, maritime risk emerges from the interaction of multiple dynamic elements, such as changing weather conditions, crew workload, traffic complexity, and vessel handling characteristics. A lack of attention to these interactions restricts the predictive power of existing risk models and may mask emergent or cascading risks. A more systematic understanding requires modelling how risk factors co-evolve across segments and how their combined effects influence accident likelihood. This study addresses this gap by incorporating cross-segment socio-technical interactions into the risk assessment framework.

3. Methodology

3.1. TAN modelling

BNs are probabilistic graphical models represented as Directed Acyclic Graphs (DAGs), in which nodes denote random variables (either discrete or continuous) and edges reflect conditional dependencies among them [54]. These relationships are quantified through Conditional Probability Tables (CPTs), which capture the likelihood of each variable given the states of its parent nodes [55]. BNs are particularly suited for integrating heterogeneous data sources, such as empirical data and expert judgment, thereby overcoming limitations associated with classical probabilistic models that often struggle with sparse or incomplete datasets. Moreover, BNs support bidirectional inference, allowing for both predictive and diagnostic reasoning [56], thus offering interpretability and insight beyond what is typically achievable through conventional statistical techniques.

The TAN model the representational capacity of standard BNs by incorporating a maximum-weight spanning tree structure among the predictor variables [57]. This structure captures dependencies between variables while preserving computational simplicity and interpretability.

To support the development of the TAN model, a bespoke global maritime accident dataset was constructed through a structured process of data fusion, completion, and quality assurance. Initial filtering removed records with insufficient detail, particularly cases involving fishing vessels, domestic ferries, or naval ships, resulting in 462 usable reports. These records were then linked to the LRF database using unique vessel identifiers (IMO number and MMSI). Cross-database matching allowed the completion of missing vessel attributes such as ship type, principal dimensions, gross tonnage, age, and hull construction. After this step, 428 records contained complete data for all 23 RIFs.

A further round of manual validation was performed to ensure consistency across accident narratives, vessel specifications, and environmental descriptors. Records lacking essential causal or contextual information were removed, yielding a final dataset of 402 accidents. Systematic range checks and cross-field consistency checks were applied throughout to minimise transcription errors and reduce potential biases associated with incomplete reporting. The resulting dataset, combining IMO GISIS accident records with normalised LRF vessel information, provides a robust and high-integrity foundation for subsequent BN-based analyses.

In the TAN model, 23 RIFs identified in prior work [58] are represented as sub-nodes capturing human, vessel, environmental, and managerial factors. The voyage segment is positioned as the root node, reflecting its fundamental role in structuring the operational context of maritime navigation. Following Bitner-Gregersen et al. [59], this variable is classified into three states: restricted waters, coastal waters, and open seas. Each RIF is conditionally dependent on the voyage segment and is discretised into relevant state categories (e.g., the "Hull Construction" node includes "Double Bottom," "Double Hull," and "Single Hull").

Fig. 1 depicts the structure of the TAN model, developed using global maritime accident data collected between 2017 and 2021 and implemented via the Netica software platform. The diagram highlights the directional dependencies between the voyage segment and the RIFs, as well as interconnections among the RIFs themselves. Each node is associated with a CPT, the parameters of which are learned directly from historical data in accordance with Bayesian inference principles. This modelling approach enables a robust and interpretable framework for understanding how voyage segments influence maritime safety and for identifying critical risk factors under varying operational conditions.

3.2. Sensitivity analysis

3.2.1. Mutual information

Mutual Information (MI) measures the dependence between two random variables, reflecting how much knowing one variable reduces uncertainty about the other [60,61]. It is related to entropy, which indicates system stability. The MI can be expressed as:

$$I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|H) \tag{1}$$

The formula for MI is:

$$I(X;Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y) log \frac{p(x,y)}{p(x)p(y)} \tag{2}$$

MI is crucial in machine learning and data analysis [62], serving several vital functions. It aids in feature selection and engineering [63] by evaluating the correlation between features and labels, identifying the most predictive features and improving model generalisation [64].

In summary, MI is essential for understanding data relationships and optimising model performance, as well as supporting research and applications across diverse fields. In this study, MI is utilised to assess the importance and priority of the RIF on the target variable. Table 3 presents the MI values between the target node 'Voyage Segment' and the RIF. The average MI value is 0.06389; RIFs exceeding this threshold are considered significant. That is, **Ship operation, Ship speed, Type of accident, Ship type, Draught, Gross tonnage**

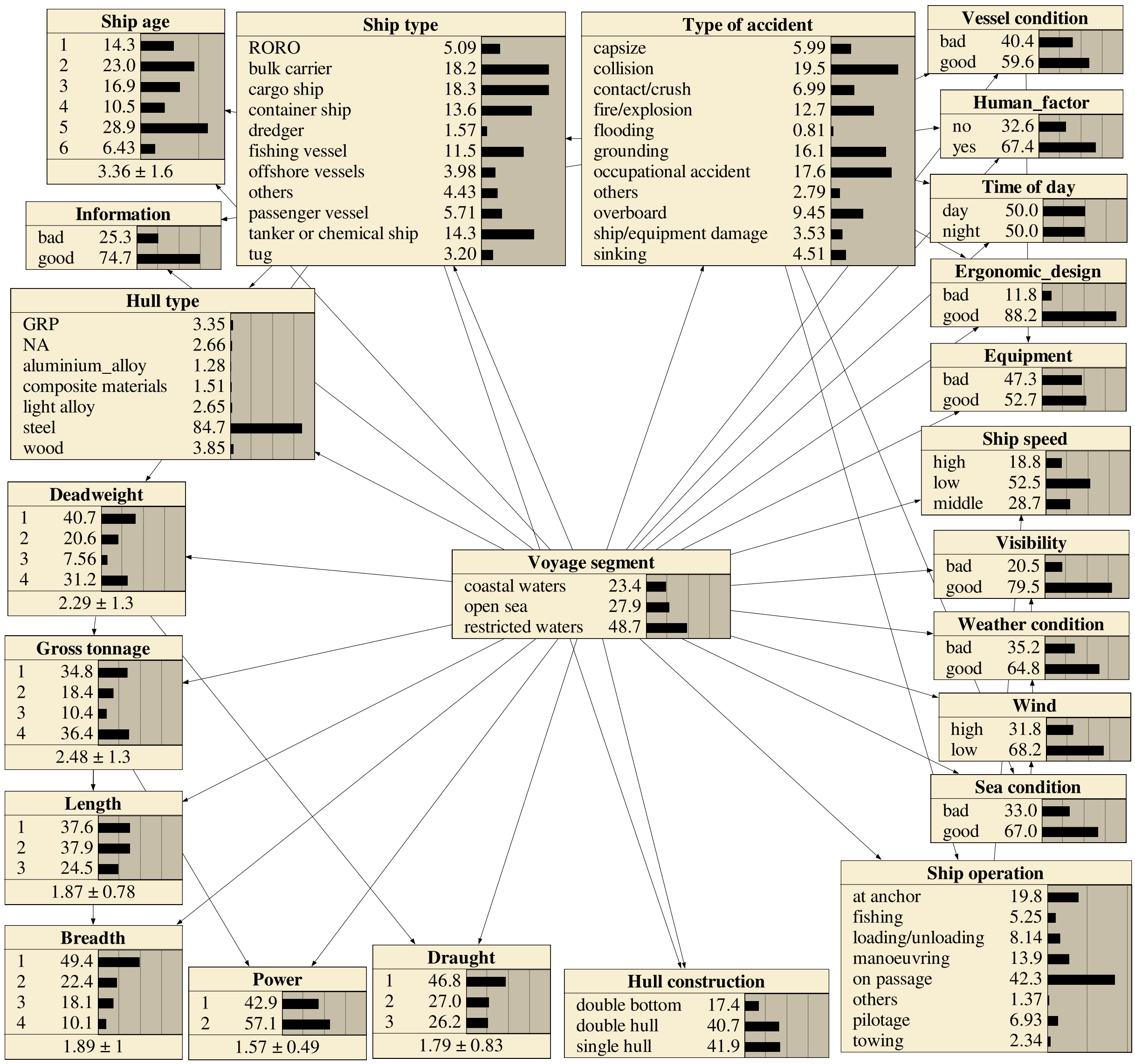

Fig. 1. The constructed TAN model.

3.2.2. *Joint probability*

After identifying the six key RIFs, a further analysis was conducted to evaluate their impact on maritime accidents across different voyage segments. This was done by setting one state of each RIF to 100 % while keeping all other variables constant, allowing the calculation of updated probabilities for each accident type [65]. Table 4 presents the results, showing how different states of six critical RIFs influence accident risks across various voyage segments. It includes both the original probability of each voyage segment and the corresponding risk levels, providing a clear view of how individual RIFs contribute to accident likelihood.

Table 4 reveals several key insights about the influence of various RIFs on different voyage segments. For instance, when 'Ship Operation' is categorised as 'Loading/Unloading', it has the highest influence on 'restricted waters' (91.506 %) and the lowest on 'coastal waters' (2.656 %). In 'open seas', the 'On Passage' operation shows a significant influence (53.497 %), while 'Manoeuvring' has minimal impact (3.378 %).

Regarding 'Ship Speed', a 'Low Speed' status shows lower influence in 'coastal' (17.086 %) and 'open seas' (9.658 %) but significantly higher influence in 'restricted waters' (73.256 %). Analysis of 'Accident Type' indicates that 'Contact/Collision' accidents are rare in 'coastal' (7.385 %) and 'open seas' (7.398 %) but much more likely in 'restricted waters' (85.218 %). On the other hand, 'Occupational Accidents' have a low probability in 'coastal waters' (1.537 %) but higher probabilities in 'open seas' (43.529 %) and 'restricted waters' (54.934 %).

These findings offer valuable insights into the causative factors of maritime accidents, providing practical guidance for safety management initiatives aimed at prevention. Analysing the influence of each RIF on voyage segments is crucial for enhancing navigation safety, mitigating risks, optimising resource allocation, and supporting informed decision-making. This area of research warrants further exploration and deeper investigation.

3.2.3. *True risk influence*

True Risk Influence (TRI) [66] is a valuable method for assessing the sensitivity of model variables by quantifying the contributions of different RIFs on specific events. Its ability to provide a clear numerical ranking of RIFs makes TRI widely applicable in decision analysis and risk management [67].

The calculation of TRI involves analysing the association between a RIF and a voyage segment, such as 'open sea', by setting each state probability of the RIF to 100 % and observing the resultant probability of the segment. The highest probability value obtained from the various states of the same RIF constitutes the High Risk Inference (HRI), highlighted as the bold value in Table 4. Conversely, the lowest value

Table 3
MI and entropy reduction analysis for 'Voyage Segment'.

Node	MI	Entropy Reduction Percent	Variance of Beliefs
Voyage segment	1.50928	100	0.410331
Ship operation	0.44838	29.7	0.086431
Ship speed	0.24429	16.2	0.048461
Type of accident	0.18603	12.3	0.026256
Ship type	0.10291	6.82	0.015441
Draught	0.07302	4.84	0.009421
Gross tonnage	0.06471	4.29	0.006425
Deadweight	0.06017	3.99	0.006322
Length	0.05495	3.64	0.005912
Hull type	0.04717	3.13	0.007652
Ship age	0.04608	3.05	0.008712
Power	0.0425	2.82	0.004094
Hull construction	0.03851	2.55	0.004314
Breadth	0.03829	2.54	0.005194
Information	0.00751	0.497	0.001074
Time of day	0.00478	0.317	0.000523
Vessel condition	0.00386	0.256	0.000412
Weather condition	0.00261	0.173	0.000537
Visibility	0.00221	0.147	0.000255
Ergonomic design	0.00046	0.0306	4.53E-05
Wind	0.00036	0.024	7.36E-05
Equipment	0.00031	0.0207	0.000047
Human factor	0.0002	0.0133	4.16E-05
Sea condition	0.00018	0.0122	3.66E-05

represents the Low Risk Inference (LRI), denoted by the underline value in the same table. The TRI value is calculated as the average of the HRI and LRI, effectively capturing the extent of influence that a specific state of an RIF has on the targeted event state. Using a similar methodology, one can derive the impact probabilities of different RIF states on the three voyage segment types. Notably, a larger probability value signifies a more significant influence of the corresponding state on the voyage segment.

Based on the calculations from Table 4, the TRI values for the six key RIFs can be computed. For example, analysing 'Accident Type' in 'open seas', the initial probability is 27.865 %. According to Table 7, various accident types are assessed under this state. The 'Fire/Explosion' accident type has the highest probability at 46.935 %, resulting in a high-risk inference difference of 19.07 % from the initial probability. Conversely, the 'Grounding' accident type shows the lowest probability at 6.266 %, yielding a low-risk inference difference of 21.599 %. The TRI for 'Accident Type' in 'open seas' is the average of these two values, resulting in 20.335 %.

The same methodology calculates TRI values for other key RIFs across different voyage segment states, as shown in Table 5. This methodology allows for ranking each RIF's influence from 1 (most significant) to 6 (least significant), as detailed in Table 6.

The analysis reveals that 'Ship Operation' has a stronger influence in 'restricted waters' and 'coastal waters' than in 'open seas'. On the other hand, 'Ship Speed' has a more substantial impact in 'open seas' and 'restricted waters' than in 'coastal waters'. Specifically, in 'restricted waters', 'Ship Operation' is the most influential RIF, while 'Gross Tonnage' is the least influential.

The overall influence hierarchy of the six critical RIFs on the 'Voyage Segment' is summarised as follows: Deadweight < Gross Tonnage < Draught < Ship Type < Ship Speed < Type of Accident < Ship Operation. This ranking suggests that "Ship Operation" has the most substantial impact on the 'Voyage Segment', while 'Deadweight' has the least significant effect.

3.2.4. *The combined influence of multiple variables*

To validate the BN model and assess the comprehensive impact of the multiple RIFs on 'Voyage Segments', a sensitivity analysis was performed on the six key RIFs identified. The reasoning process for sensitivity analysis adheres to two fundamental axioms [68]:

Axiom 1: Each small increment or decrement in each RIF should correspondingly affect the posterior probability of the target node.

Axiom 2: The collective effect of multiple RIFs' small increments on the probability of the target node should not be less than the effect of a single RIF.

To ensure that the model's combined effects are accurate, the study treats the six key RIFs as a subset of variables, using 'Voyage Segments'

Table 4
The combined influence of multiple variables.

	coastal waters	open sea	restricted waters
original	23.391	27.865	48.745
Ship operation			
at anchor	7.852	6.947	85.201
fishing	**56.522**	30.048	13.430
loading/unloading	2.656	5.839	**91.506**
manoeuvring	15.276	6.477	78.246
on passage	35.342	**53.497**	11.161
others	15.726	33.357	50.917
pilotage	6.581	3.378	90.041
towing	39.385	10.010	50.605
Ship speed			
high	25.334	**63.129**	11.536
low	17.086	9.658	**73.256**
middle	**33.640**	38.048	28.312
Type of accident			
capsize	**53.799**	12.753	33.448
collision	36.611	30.372	33.017
contact/crush	7.385	7.398	**85.218**
fire/explosion	19.637	**46.935**	33.429
flooding	3.018	33.255	63.727
grounding	27.615	6.266	66.119
occupational accident	1.537	43.529	54.934
others	27.371	45.107	27.522
overboard	23.677	18.505	57.818
ship/equipment damage	28.590	28.639	42.771
sinking	27.800	38.767	33.433
Ship type			
RORO	16.708	32.260	51.032
bulk carrier	15.356	37.827	46.817
cargo ship	25.626	14.007	60.368
container ship	14.220	39.028	46.752
dredger	27.570	14.164	58.266
fishing vessel	40.911	28.697	30.392
offshore vessels	**42.340**	9.790	47.870
others	36.229	5.033	58.738
passenger vessel	13.989	7.377	**78.634**
tanker or chemical ship	20.750	**44.978**	34.272
tug	28.068	13.719	58.213
Draught			
1	**31.870**	15.020	**53.109**
2	17.079	31.006	51.915
3	14.773	**47.517**	37.710
Gross tonnage			
3	**35.525**	13.008	51.467
4	19.453	30.303	50.243
2	18.270	28.145	**53.584**
1	15.259	**40.736**	44.005
Deadweight			
1	**32.124**	14.130	**53.746**
2	20.873	30.772	48.356
3	15.904	36.011	48.085
4	15.477	**41.887**	42.636

Table 5
TRI of RIFs for all.

	Coastal waters	Open seas	Restricted waters
Ship operation	26.933	25.060	40.173
Ship speed	8.277	26.736	30.860
Type of accident	26.131	20.335	28.848
Ship type	14.176	19.973	24.121
Draught	8.549	16.249	7.700
Gross tonnage	10.133	13.864	4.790
Deadweight	8.324	13.879	5.555

Table 6
The most important RIFs for all.

	Coastal waters	Open sea	Restricted waters
Ship operation	1	2	1
Ship speed	7	1	2
Type of accident	2	3	3
Ship type	3	4	4
Draught	5	5	5
Gross tonnage	4	7	7
Deadweight	6	6	6

as the parent node. Given that the parent node has multiple states, the analysis focuses on how probability values change for each state. For instance, when analysing 'Total Tonnage', the probability changes for 'open seas' are examined by increasing the states with the greatest and smallest influences (specifically '4'and '1'from Table 4) by 2 %. The resulting probability change for 'open seas' is observed and calculated. This procedure is replicated for 'coastal waters' and 'restricted waters', applying a similar methodology to evaluate the cumulative impact of the six key RIFs on 'Voyage Segments'. Specifically, cumulative updates are performed sequentially through the RIFs: 'Deadweight', 'Gross Tonnage', 'Draught', 'Ship Type', 'Ship Speed', 'Type of Accident', and 'Ship Operation', culminating in the cumulative probability changes presented in Table 7.

An analysis of adjacent columns in Table 7 demonstrates that with minor increments in RIFs, there is a corresponding increase in the probability values of each state of the parent node, 'Voyage Segments'. These findings support Axiom 1, demonstrating that changes in the prior probability of variable nodes result in corresponding changes in the posterior probability of the target node. Additionally, by comparing the values in the last three rows of Table 7, as the effects of multiple RIFs accumulate, the probability values for each state of the parent node increase steadily. This cumulative effect surpasses the influence of any individual RIF and reinforces Axiom 2, showing a consistent upward trend in the target node's probability values as RIFs are progressively updated.

In summary, by confirming Axioms 1 and 2, the analysis establishes the correctness of the BN model, quantitatively demonstrating the comprehensive impact of multivariate factors on the parent node 'Voyage Segments'.

To further examine the sensitivity of the TAN model, we assessed how incremental changes in key RIFs affect the posterior probability of the parent node, Coastal Waters. The baseline probability of the coastal-waters state was 23.391 %. Following the update procedure described earlier, the influence of the two most impactful RIFs, Ship Operation and Ship Speed, was evaluated sequentially.

An increase of 5 % in the probability of the relevant Ship Operation state produced a corresponding rise in the posterior probability of coastal waters from 23.391 % to 26.084 %. Similarly, increasing the probability of the Ship Speed state by 5 % elevated the coastal-waters probability to 24.218 %. These results show that relatively small perturbations in key RIFs yield measurable and directionally consistent changes in the posterior distribution of the voyage-segment node.

This analysis demonstrates that the TAN model exhibits appropriate sensitivity to variations in influential factors, confirming that the probabilistic structure captures the dependencies between RIFs and voyage segments in a coherent and interpretable manner. The findings provide quantitative evidence of the robustness of the inference process and the model's ability to reflect the effects of multiple interacting contributors to maritime navigational risk.

3.2.5. Model validation

The classification capability of the TAN model across the three navigational environments was evaluated using the confusion matrix shown in Fig. 2. The results indicate that the model performs consistently well across all classes. For coastal-waters accidents, all 9 cases were correctly classified, demonstrating perfect recognition for this category. For open-sea accidents, 10 of the 11 cases were correctly identified, with only one misclassified as restricted waters. Restricted-waters accidents were also captured with high accuracy: 18 out of 20 cases were correctly assigned, while two were incorrectly classified as coastal waters. Overall, the model correctly predicted 37 out of 40 accidents in the validation sample, indicating strong classification reliability.

The quantitative performance metrics in Table 8 corroborate these findings. Precision values of 0.818 (coastal waters), 1.000 (open sea), and 0.947 (restricted waters) show that the majority of model predictions within each class are correct. Recall values, 1.000 for coastal waters, 0.909 for open sea, and 0.900 for restricted waters, demonstrate that the model successfully identifies most true cases in each category. The corresponding F-measures of 0.900, 0.952, and 0.923 reflect a consistently strong balance between precision and recall.

Taken together, these validation results confirm that the TAN model achieves robust and stable classification performance across all navigational environments. The high precision–recall balance indicates that

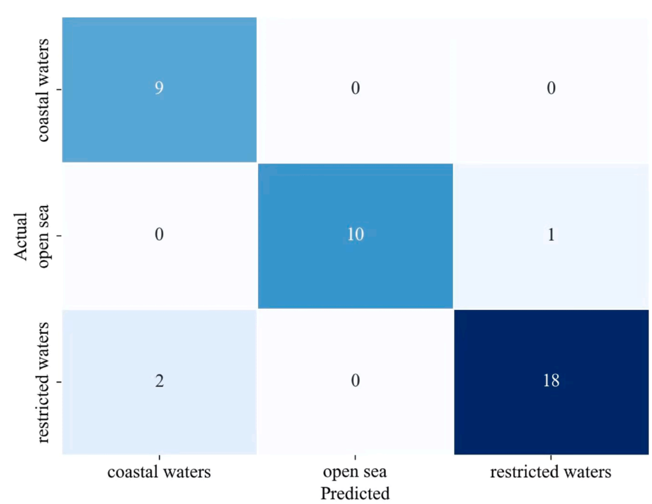

Fig. 2. Confusion matrix for TAN model classification.

Table 7
The combined influence of multiple variables.

Deadweight		+2 %	+2 %	+2 %	+2 %	+2 %	+2 %	+2 %
Gross tonnage			+2 %	+2 %	+2 %	+2 %	+2 %	+2 %
Draught				+2 %	+2 %	+2 %	+2 %	+2 %
Ship type					+2 %	+2 %	+2 %	+2 %
Ship speed						+2 %	+2 %	+2 %
Type of accident							+2 %	+2 %
Ship operation								+2 %
coastal waters	23.391	23.723	24.129	24.475	25.039	25.392	26.437	27.538
open sea	27.865	28.420	28.977	29.623	30.422	31.538	32.380	33.470
restricted waters	48.745	48.967	49.155	49.465	50.437	51.670	52.813	54.409

Table 8
Performance metrics for TAN classification results.

	coastal waters	open sea	restricted waters
precision	0.818	1	0.947
recall	1	0.909	0.9
F-measure	0.9	0.952	0.923

the model effectively captures the distinguishing characteristics of accidents occurring in restricted waters, coastal waters, and the open sea. This level of performance provides confidence in the model's suitability for subsequent probabilistic risk assessment and forecasting analyses within the maritime safety domain.

4. Results and implications

4.1. Scenario analysis

Specific voyage segments are critically analysed, representing vital pathways for vessels. Various scenarios, weather changes, human factors, maritime conditions, and vessel statuses, are simulated to assess their impact on voyage segments. Accident types are simulated, and RIF states are identified using BN models with TAN.

This approach reveals the risks specific to each voyage segment under different conditions. For example, simulating adverse weather highlights the most likely accident types, offering early warnings for maritime authorities. Similarly, analysing human factors uncovers risk distributions, helping target preventive actions.

These insights allow authorities to develop tailored accident prevention strategies, including enhanced crew training, improved vessel design and maintenance, optimised routes, and adjusted schedules to minimise risks and ensure safer navigation.

4.1.1. Risk analysis by individual voyage segment

A segment-specific risk analysis was conducted to evaluate how operational behaviours and accident probabilities vary across different maritime environments when the probability of each voyage segment is individually set to 100 %.

The simulation results of coastal navigation (Fig. 3) revealed distinct operational patterns and risk shifts. When vessels were assigned exclusively to coastal waters, the probability of being 'On Passage' increased significantly from 42.3 % to 63.9 %. This transition coincided with a higher likelihood of large vessel presence, as indicated by elevated probabilities for 'Gross Tonnage' and 'Draught'. Greater accessibility to

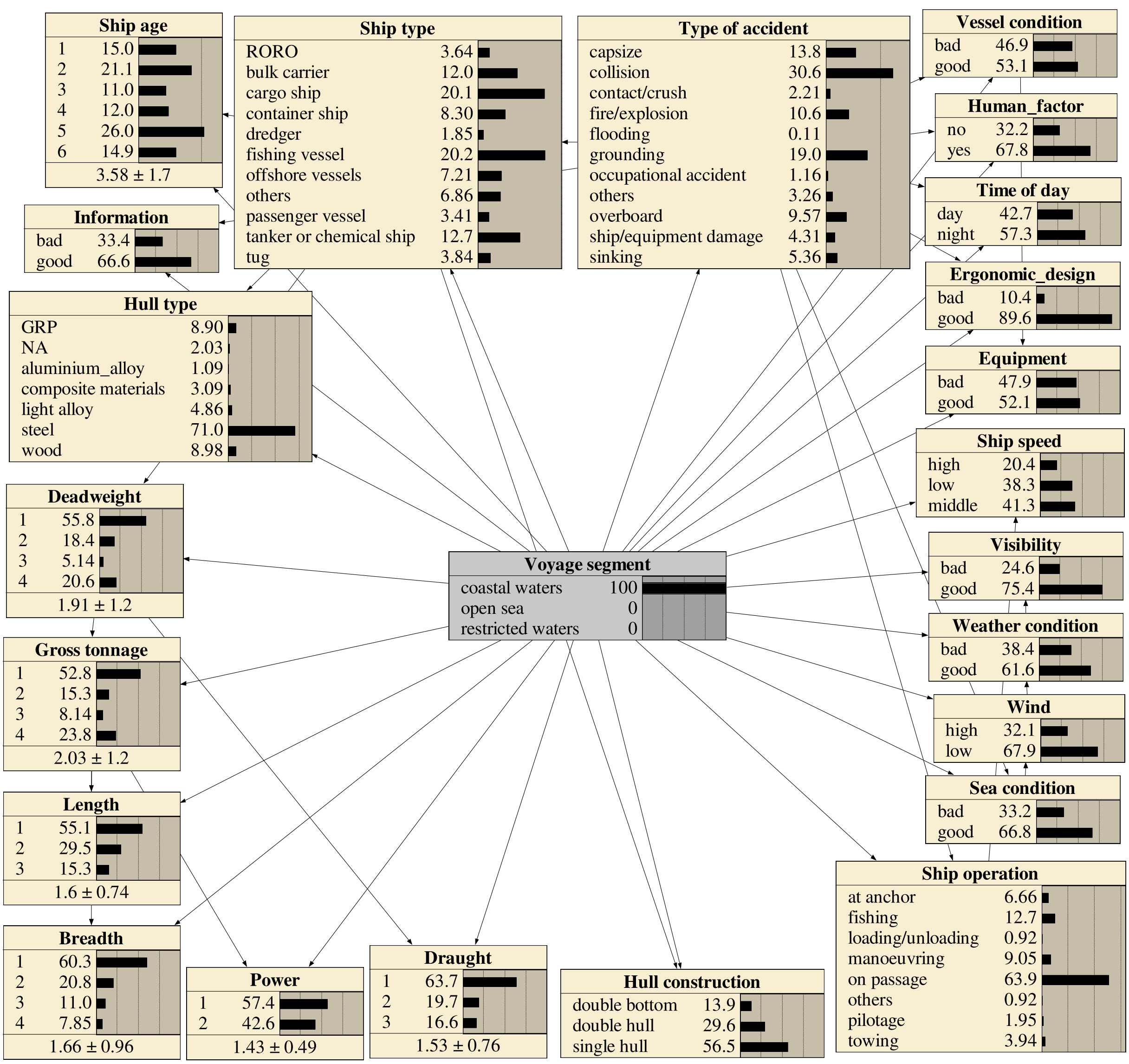

Fig. 3. The most likely scenario for coastal waters.

port infrastructure is associated with smoother and more controlled transit for larger vessels operating in these waters. Notably, the probability of occupational accidents decreased markedly from 17.6 % to 1.16 %, suggesting that well-developed port facilities, enhanced navigational services, and established emergency-response systems are strongly predictive of reduced crew-related hazards. These findings underscore the need to further enhance channel design and port infrastructure to support the growing volume of large vessels operating in coastal regions. It also reflects the recent accidents in the Seuz Canal blockage and the Blatimore bridge collision, all in narrow waters.

In open sea conditions (Fig. 4), the model indicated a marked increase in 'On Passage' operations (rising to 81.1 %) and a substantial reduction in low-speed manoeuvres (from 52.5 % to 18.2 %), reflecting greater navigational freedom. This shift was accompanied by a preference for medium to high-speed transits, aligned with the efficiency-driven nature of long-haul shipping routes. While the probability of grounding accidents decreased significantly (from 16.1 % to 3.63 %), the likelihood of occupational accidents (17.6 % to 27.5 %) and fire/explosion events (12.7 % to 21.3 %) rose notably. These elevated risks are associated with extended exposure to harsh sea conditions, mechanical fatigue, cumulative crew stress, and a reduced state of operational readiness. In deep-sea operations, machinery is often left in Unattended Machinery Spaces (UMS) mode with fewer crew actively monitoring equipment, in contrast to restricted or coastal waters where vessels typically operate under standby conditions with more personnel on duty. These findings highlight the critical need for robust fire safety protocols, comprehensive crew fatigue management programmes, and predictive maintenance systems to enhance vessel resilience and safety during prolonged operations in open seas.

Navigating restricted waters introduced a distinct operational profile (see Fig. 5), characterised by a high probability of low-speed movement (78.9 %) and frequent anchoring (34.7 %). In contrast, the likelihood of being 'On Passage' dropped to just 9.68 %, reflecting cautious navigation in congested or geographically constrained areas. Despite the operational complexity, accident probabilities remained relatively stable, suggesting that existing control measures, such as speed limits, anchorage regulations, and local traffic monitoring, effectively mitigate risk. Nonetheless, the high anchoring frequency highlights the importance of regular mooring system maintenance and efficient traffic coordination to avoid equipment failures, congestion, or secondary accidents. Table 9 summarises the impacts and results of different voyage segments. This analysis shows that voyage segments significantly shape vessel behaviours and associated risk profiles. Coastal waters benefit from infrastructure-based safety enhancements but face

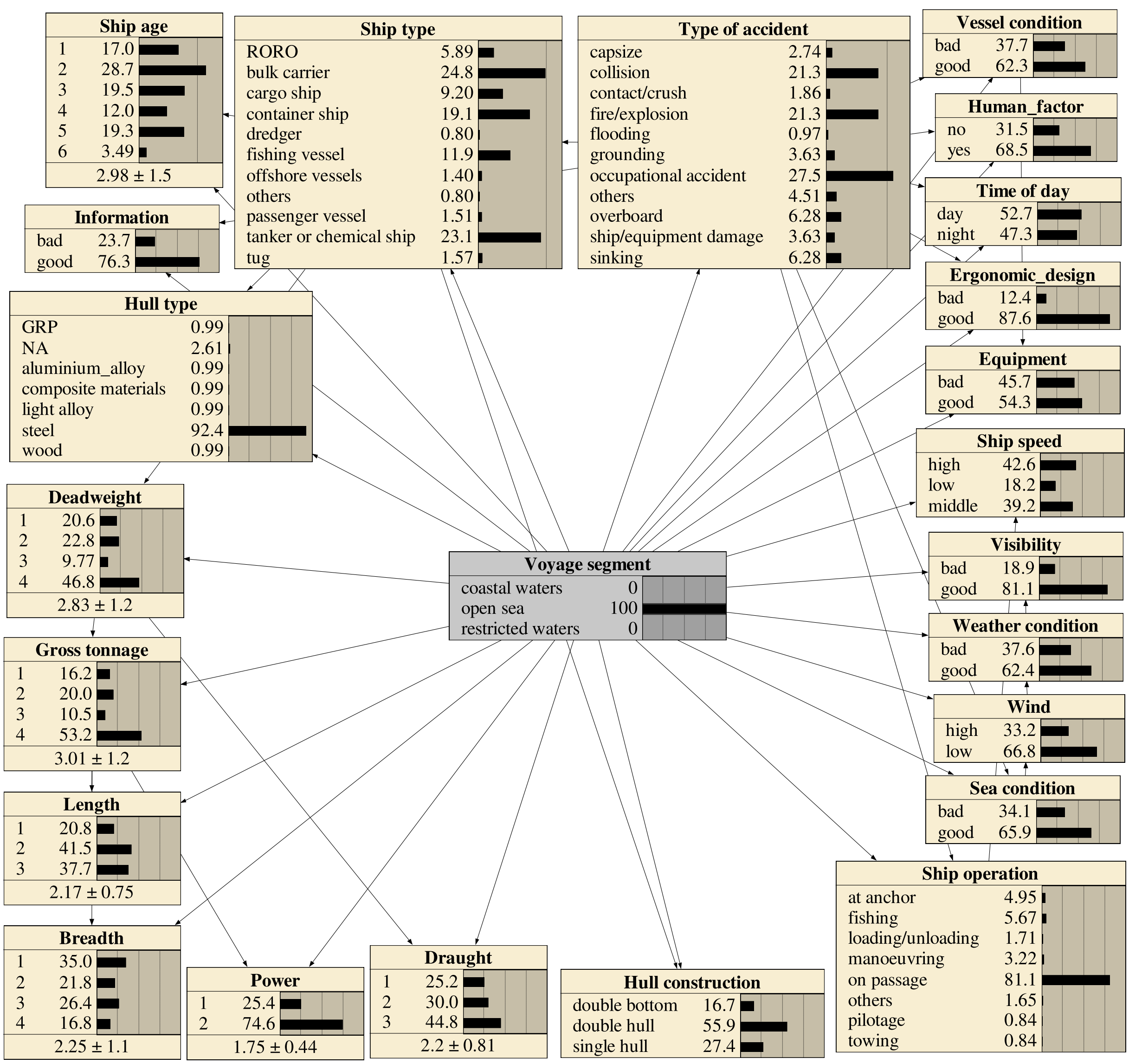

Fig. 4. The most likely scenario for open sea.

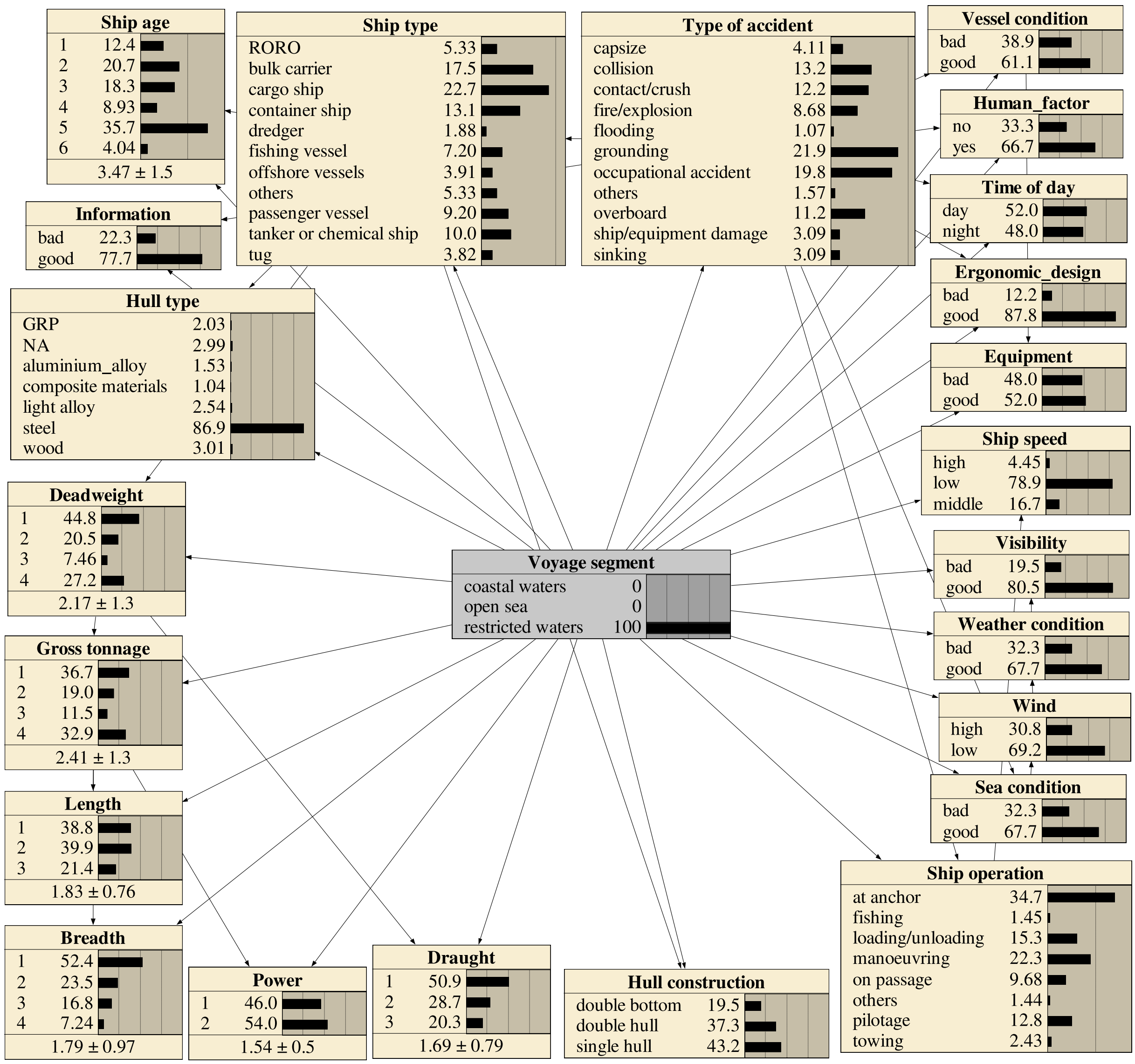

Fig. 5. The most likely scenario for restricted waters.

growing capacity demands. Open sea operations introduce increased exposure to occupational and mechanical risks, necessitating resilience-focused interventions. Restricted waters rely heavily on procedural enforcement to manage safety in high-density zones. Recognising and responding to these segment-specific dynamics is essential for the development of targeted safety management strategies and more effective maritime corridor design.

4.1.2. Comparative analysis of risk profiles across voyage segments

A comparative assessment of voyage segments highlights both common risk drivers and unique challenges shaped by their respective operational environments. Vessel-related attributes and human factors consistently emerged as dominant contributors to maritime risk across all segments (Fig. 6). Larger vessels, particularly those exceeding 3000 gross tonnage, were more frequently observed in coastal and open sea operations, increasing the likelihood of grounding accidents in shallow or congested waters. Meanwhile, human factors, including poor ergonomic design and inadequate information flow, were associated with increased occupational accident risk, with coastal waters exhibiting a rise in probability from 17.6 % to 47.4 % under adverse conditions. Ship specifications and operating conditions played a pivotal role in determining segment-specific risk profiles. As illustrated in Fig. 7, dredgers constructed with steel hulls, possessing draughts between 0–6 m and deadweight capacities of 5000–15,000 tonnes, experienced a substantial increase in their probability of operating in restricted waters from 48.7 % to 99.4 %. These vessels also exhibited an elevated occupational accident risk of 72.2 % when engaged in loading and unloading activities. These results suggest that specific vessel configurations and cargo-handling operations are associated with heightened exposure to confined navigation spaces and crew safety hazards, potentially linked to limitations in safety measures or equipment during complex manoeuvres.

Segment-level risk patterns revealed the distinct operational demands associated with each navigational context. Coastal waters, although supported by advanced port infrastructure that helps mitigate occupational accidents, faced intensified traffic complexity resulting from dense maritime activity. In contrast, open sea operations were associated with reduced grounding risks but exhibited higher probabilities of fire and explosion events, which are predictive of extended voyage durations, increased mechanical loads, and fatigue-related factors. Restricted waters, while effectively minimising collision risks through speed regulations and anchoring protocols, encountered operational inefficiencies, with vessels navigating at low speeds nearly 78.9 % of the time.

Table 9
The impacts and results of different voyage segments.

Voyage segment	Vessel status	Risk changes	Findings
Coastal waters	Frequent vessel operations, more vessels in 'on passage' status.	Occupational accident probability significantly decreases (from 17.6 % to 1.16 %) due to convenient port facilities.	The busy shipping activity in coastal waters necessitates improvements in navigation channels and port facilities to ensure safety.
Open seas	More vessels in 'on passage' status, higher speeds.	Grounding probability significantly decreases (16.1 % to 3.63 %), but occupational accidents and fire/ explosion risks increase (occupational accidents from 17.6 % to 27.5 %).	While certain risks decrease, new safety challenges arise, requiring enhanced occupational safety management.
Restricted waters	Vessels are mostly at anchor, lower speeds (low-speed probability increases from 52.5 % to 78.9 %).	Maritime accident risks remain relatively stable, showing no significant increase or decrease.	Effective safety regulations and navigation measures ensure safe vessel operations in restricted waters.

Environmental factors also demonstrated differential impacts across voyage segments (Fig. 8). Adverse meteorological and oceanographic conditions, including reduced visibility, high winds, and rough seas, were associated with higher probabilities of grounding in constrained environments. In coastal and restricted waters, grounding probabilities increased from 16.1 % to 30.8 % under such conditions. By contrast, vessels operating in open sea environments displayed greater resilience to environmental variability, with associated accident risks remaining relatively stable despite deteriorating weather. This disparity underscores the interaction between geographic constraints and operational flexibility, highlighting the need for risk mitigation strategies that are tailored to both shared vulnerabilities and segment-specific conditions.

4.1.3. Common risks between transitional voyage segments

Transitions between voyage segments introduce dynamic operational shifts and emergent risk profiles that require anticipatory risk management strategies. These transitional phases are particularly sensitive, as they involve abrupt changes in vessel behaviour, system demands, and crew workload, all of which can influence accident likelihood.

The transition from coastal waters to the open seas (Fig. 3–Fig. 4) is typically characterised by an increase in vessel speed and a shift toward sustained 'On Passage' navigation. While this change enhances transit efficiency, it also introduces elevated risks, particularly for fire and explosion accidents. The probability of such accidents increases from 10.6 % in coastal waters to 21.3 % in open sea conditions, which is associated with prolonged engine operation, increased mechanical loading, and heightened fuel system activity. To mitigate these risks, it is essential to implement pre-transition safety protocols, including mechanical inspections, fire safety checks, and crew readiness assessments. For instance, when a ship is ready to start a deep-sea voyage by leaving a canal, the captain and his team will need to pay extra attention on the suggested risks found in this study along with their routine safety checking on the existing practices.

Transitions from open seas to restricted waters (Fig. 4–Fig. 5) demand rapid deceleration and increased manoeuvring precision. The probability of low-speed operations rises sharply from 18.2 % to 78.9 %, reflecting the need for heightened navigational control in confined or congested environments. Such abrupt reductions in speed impose additional loads on propulsion and steering systems, which in turn are predictive of an elevated likelihood of mechanical failure if these systems are not properly tuned or maintained. At the same time, the probability of anchoring operations increases from 19.8 % to 34.7 %, highlighting that proactive maintenance and inspection of anchoring equipment are strongly associated with reduced risks of equipment malfunction, anchor dragging, and collision events in high-traffic or constrained navigational zones.

The effective management of transition-related risks relies on dynamic, real-time risk assessment frameworks that integrate environmental, technical, and human factors. Crew preparedness is critical; navigators must be trained to manage sudden operational changes, such as rapid speed adjustments, engine reconfigurations, and anchoring procedures, while maintaining situational awareness and compliance with local regulations. The adoption of standardised transition protocols, such as pre-entry checks for propulsion and steering systems before entering restricted waters, or fire safety drills prior to entering open seas, can be predictive of reduced accident probabilities.

By recognising transitions as high-risk operational phases and implementing structured mitigation strategies, maritime operators and regulatory bodies can achieve outcomes associated with improved safety across interconnected voyage segments and reduced probabilities of disruptions, delays, or cascading failures within the maritime transport system.

4.1.4. Integrated, system-level strategies for maritime corridor safety

Improving safety across maritime corridors requires a system-level approach that integrates vessel design, crew preparedness, infrastructure capability, data-driven risk analytics, and regulatory coordination. Maritime corridors function as multi-segment socio-technical systems; therefore, safety interventions must address both segment-specific hazards and the interdependencies that drive risk propagation across the voyage.

A foundational element of corridor safety is the optimisation of vessel architecture. Enhancements to hull form, propulsion performance, steering responsiveness, and redundancy in critical systems enable vessels to maintain adaptive performance across diverse operating environments. For instance, vessels must sustain efficient high-speed transit in open-sea conditions while retaining precise manoeuvring capability when navigating restricted or congested waters. Such design considerations strengthen the vessel's intrinsic resilience to operational variability.

Human performance remains central to corridor safety. Crew competence should be supported through scenario-based training that reflects transitions between navigational segments, including emergency deceleration when approaching port limits, anchoring under high-density traffic conditions, or manoeuvring in environmentally constrained waters. These targeted simulation exercises enhance situational awareness, improve human reliability, and reduce the likelihood of operator-induced failures during dynamic operational changes.

Infrastructure capability further underpins system resilience. In coastal regions, expanded port capacity, improved traffic-management systems, and modernised cargo-handling technologies can alleviate bottlenecks and reduce delay propagation. Open-sea corridors benefit from strengthened emergency-response capacity, including mobile rescue units, interoperable communication platforms, and real-time information-sharing systems. Segment-specific infrastructure improvements reduce the consequences of equipment failures, navigational anomalies, and environmental disruptions, thereby limiting the escalation of local disturbances into system-level failures.

Data-driven risk analytics provide a proactive mechanism for identifying emerging hazards and managing corridor-wide risks. BN approaches enable probabilistic inference of risk propagation across segments, such as the downstream effects of anchorage congestion or delays in vessel transitions. Such models can inform optimal traffic

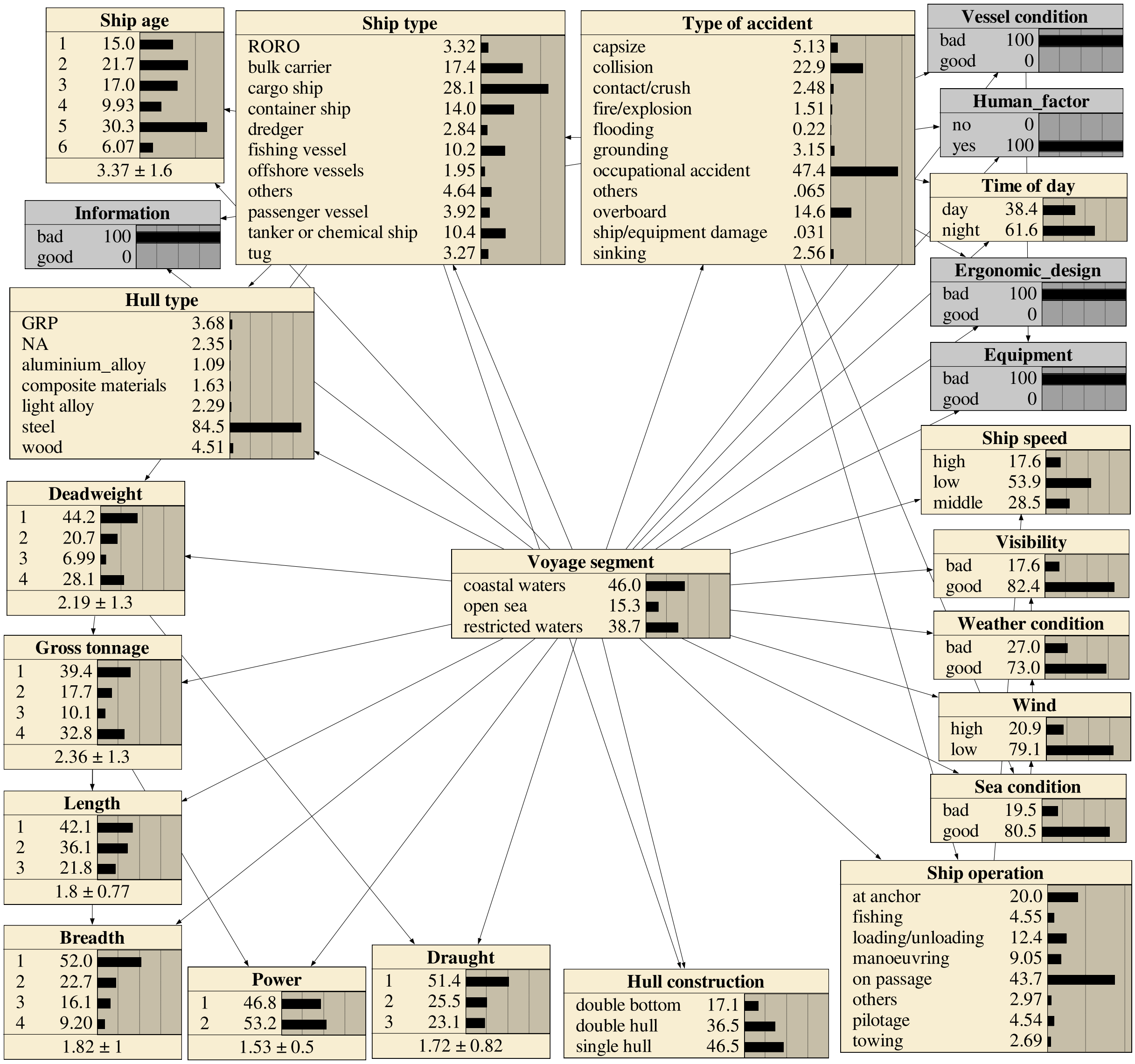

Fig. 6. The most likely scenario for specific people- and ship-related factors.

scheduling, routing adjustments, emergency-resource allocation, and the prioritisation of high-risk vessels. Predictive maintenance systems tailored to segment-specific stressors, such as prolonged engine loads in open seas or frequent stopping manoeuvres in restricted waters, support early detection of degradation, improving equipment reliability and reducing the likelihood of sudden failures.

Regulatory harmonisation is also essential for ensuring coherent risk control across jurisdictional boundaries. Standardised navigational protocols, such as speed policies, anchorage procedures, and mandatory reporting during segment transitions, reduce operational ambiguity and enhance compliance in international maritime corridors. Furthermore, the implementation of real-time environmental monitoring systems in high-risk zones supports adaptive route planning and enables timely hazard mitigation, particularly in regions characterised by rapid weather variability or visibility loss.

In summary, an effective maritime corridor safety strategy must integrate technological, human, infrastructural, analytical, and regulatory dimensions within a unified systems framework. Addressing both segment-specific risks and cross-segment interdependencies enhances operational reliability, reduces the potential for cascading failures, and contributes to a more resilient maritime safety management system.

4.2. Implications

This study presents a segment-specific risk assessment framework based on scenario analysis, offering detailed insights into how operational patterns and accident probabilities vary across coastal waters, open seas, and restricted waters. The findings support more precise risk mitigation, vessel design, policy formulation, and operational decision-making in maritime safety management. The key implications are outlined below:

(1) Segment-specific risk patterns require targeted safety strategies. The scenario analysis revealed that each voyage segment is characterised by unique risk profiles shaped by vessel behaviour and environmental constraints. In coastal waters, the probability of vessels being ‘On Passage’ rose from 42.3 % to 63.9 %, while occupational accident risk sharply decreased from 17.6 % to 1.16 %, suggesting infrastructure and port services are associated with reduced human-related accidents. In contrast, open sea conditions showed an increase in ‘On Passage’ status to 81.1 % and a drop in low-speed manoeuvres, but accident probabilities related to occupational hazards (17.6 % to 27.5 %) and fire/explosion (12.7 % to 21.3 %) rose significantly. In restricted waters,

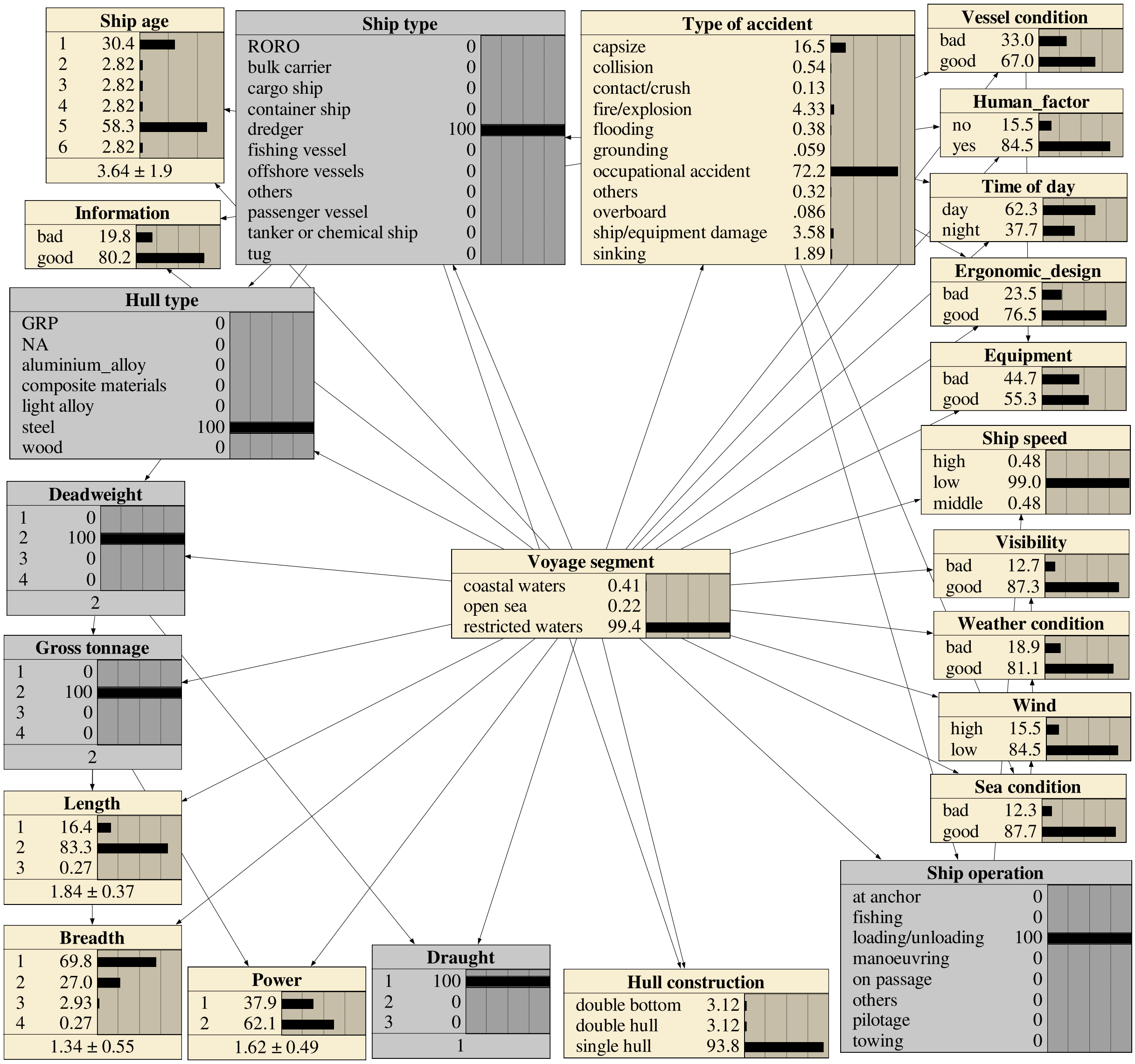

Fig. 7. The most likely scenario for specific ship-related factors.

anchoring and low-speed navigation dominated (anchoring at 34.7 %, low-speed at 78.9 %), yet accident rates remained stable due to effective regulations.

These results confirm the need for segment-specific safety strategies. For instance, reinforcing port infrastructure in coastal zones, improving fire safety protocols and crew fatigue management in open seas, and enhancing mooring system reliability and anchoring safety in restricted waters.

(2) Environmental and human factors must be addressed together.

Environmental stressors, such as reduced visibility, rough sea states, and high wind speeds, are strongly associated with elevated grounding probabilities in both coastal and restricted waters (e.g., increasing from 16.1 % to 30.8 %), underscoring the critical influence of environmental conditions on maritime risk. Model simulations for restricted waters further indicate that a 20 % increase in the likelihood of adverse weather is associated with a 0.29 % rise in the probability of overboard incidents. By comparison, a 20 % increase in human-factor involvement produces a substantially larger effect, increasing the likelihood of overboard incidents by 2.86 %. These results suggest that both environmental and human stressors contribute meaningfully to accident risk, with human-related factors demonstrating a stronger marginal effect in this scenario.

When environmental hazards cannot be avoided, human-centred interventions become essential safeguards. Measures such as enhancing bridge ergonomics, integrating real-time navigational and weather-information systems, and providing targeted training in workload and stress management can mitigate the operational impact of environmental variability. Findings from coastal-waters scenarios further indicate that, even where infrastructure is well developed, accident causation remains highly sensitive to human performance, reinforcing the need for integrated strategies that account for both environmental and human elements within maritime operations.

(3) Vessel characteristics strongly influence accident likelihood.

The scenario-based analysis identified vessel-specific risk patterns. For example, dredgers with steel hulls and draughts of 0–6 m under loading conditions were highly likely to operate in restricted waters (48.7 % to 99.4 %) and exhibited elevated occupational accident risks (72.2 %). The influence of vessel deadweight on grounding risk was further quantified: increasing deadweight to level 1 (representing large vessels) raised the likelihood of grounding by 20 %, while reducing deadweight to level 4 (small vessels) decreased it by 20 %. On this basis, the

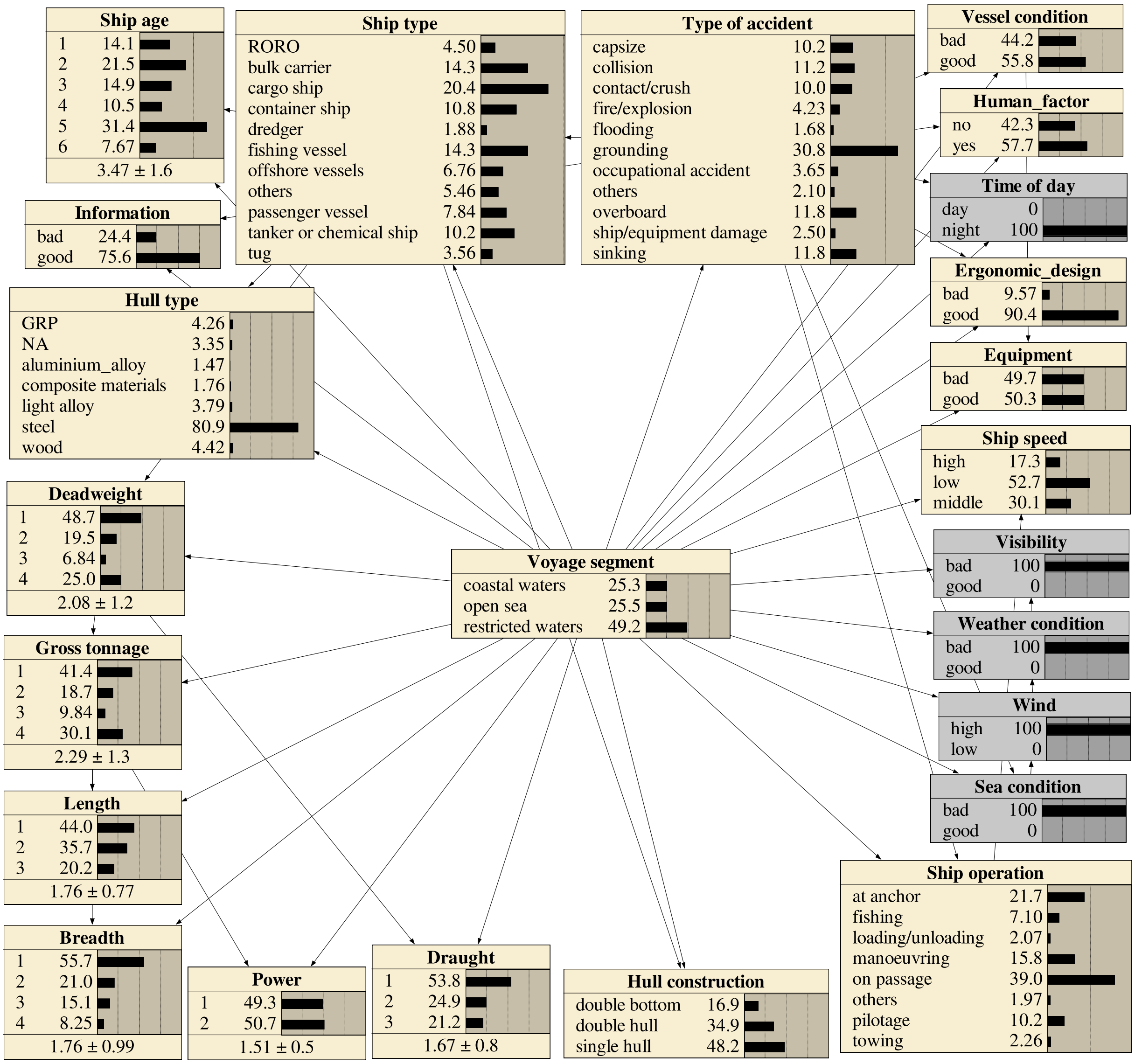

Fig. 8. The most likely scenario for specific people-related factors.

adjusted grounding probability for large vessels reached 1.16 %, illustrating the sensitivity of grounding incidents to vessel size and operational segment. These findings highlight the importance of incorporating vessel-specific characteristics into risk-informed decision-making across different voyage segments.

These insights highlight the importance of segment-informed vessel design. Designers and shipyards should factor in segment-specific operational demands, such as draught, deadweight, hull type, and expected manoeuvring patterns, early in the design and retrofitting process to improve safety and align with sustainability and compliance needs.

(4) A predictive framework enables proactive safety management.

The study identified 23 RIFs, with six (i.e., ship operation, ship speed, accident type, ship type, draught, and gross tonnage) showing the highest sensitivity across segments. The probabilistic framework developed enables bidirectional reasoning: it can predict the likelihood of specific accidents in a given segment or determine which segments are prone to particular accident types.

This framework supports the creation of risk forecasting tools for maritime authorities. It allows for targeted inspection scheduling, segment-specific resource allocation (e.g., tug services or emergency response readiness), and prioritised safety interventions based on real-time operational context.

(5) Segment transitions introduce dynamic and often overlooked risks.The simulation results showed that transitions between voyage segments pose new safety challenges. For instance, moving from coastal to open sea increased fire/explosion risk (10.6 % to 21.3 %) due to mechanical stress from higher engine loads. Using the TAN model, it was further observed that increasing the proportion of vessels with a "bad" condition by 20 % led to a 2.73 % rise in the probability of fire/explosion incidents, emphasising the interaction between mechanical reliability and segment transitions. While transitioning from open seas to restricted waters is associated with abrupt deceleration (low-speed operation from 18.2 % to 78.9 %) and higher anchoring demand (19.8 % to 34.7 %).

Implication: These transitions require predefined safety protocols such as engine recalibration, fire safety drills, and anchoring system checks. Training crews to handle sudden operational shifts at segment boundaries is essential to prevent equipment failures and operational delays.

(6) A segment-based model fills the gaps in conventional risk analysis.

Unlike traditional models that assess risk uniformly across entire voyages, this study provides granular, segment-level analysis that captures the variability in operational and environmental conditions. This enables more accurate safety predictions and better-informed decision-making.

Implication: By focusing on localised risk conditions, maritime stakeholders can move beyond one-size-fits-all safety policies and implement data-driven, adaptive interventions that reflect real-world operational diversity. This is especially important in high-traffic or high-risk corridors where uniform strategies may overlook segment-specific vulnerabilities.

5. Conclusions

This study develops a systematic, segment-oriented framework for maritime risk analysis that enhances understanding of how accident types, human performance, vessel characteristics, and environmental conditions interact across distinct navigational contexts. By conceptualising coastal waters, open seas, and restricted waters as discrete operational domains, the analysis demonstrates that maritime risk is inherently context-dependent and shaped by both static vessel features and dynamic operational behaviours.

Using a data-driven BN model, supported by TAN structure learning, sensitivity analysis, and confusion-matrix-based validation, the study quantifies the influence of 23 RIFs. The model exhibits strong predictive accuracy and high interpretability, confirming its suitability for capturing complex interdependencies in maritime accident causation. Scenario simulations reveal distinct segment-specific risk patterns:

(1) Coastal waters show reduced occupational accident likelihood due to mature port infrastructure, yet remain vulnerable to human-factor-related risks in dense traffic environments.
(2) Open seas exhibit lower grounding probability but increased susceptibility to occupational hazards and fire/explosion events, reflecting prolonged navigation and mechanical loading.
(3) Restricted waters remain sensitive to risks arising from frequent anchoring, low-speed manoeuvring, and constrained manoeuvrability despite stringent navigational controls.

A key insight from the analysis is the elevated risk encountered during transitional phases between voyage segments. Transitions, such as from coastal waters to the open sea or from the open sea to restricted waters, introduce abrupt operational changes that can increase stress on propulsion systems, elevate crew workload, and reduce mechanical reliability. These findings underscore the need for transition-specific safety procedures and enhanced operational planning.

The proposed framework offers practical value for maritime stakeholders. Through both forward and backward inference, it enables prediction of accident types under specific navigational conditions and the identification of high-risk operational contexts based on observed or emerging indicators. This bidirectional reasoning capability provides maritime authorities, vessel operators, and infrastructure planners with granular, actionable insights to support strategic decision-making, regulatory oversight, and real-time operational risk management.

Despite its strengths, the study is constrained by the characteristics of the available data. The curated dataset of 402 accidents limits statistical coverage across vessel classes, environmental regimes, and geographical regions. Variability in national reporting standards and the exclusion of under-documented vessel categories introduce further representativeness limitations. These constraints should be considered when interpreting the generalisability of the results.

Future research will prioritise the collection of more recent, higher-resolution operational and environmental data and the integration of advanced text-mining techniques to extract richer causal information from full accident narratives. The combined use of Large Language Models (LLMs) and BN represents a promising methodological direction. LLMs can support consistent extraction and coding of RIFs, reduce subjectivity in narrative interpretation, and generate more informative structural or probabilistic inputs for BN construction. Such integration has the potential to address current limitations related to data sparsity, manual variable processing, and restricted contextual representation, thereby improving both the predictive performance and explanatory depth of maritime risk assessment frameworks.

Acknowledgements

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (Grant Agreement No 864724).

CRediT authorship contribution statement

Yiheng Wu: Writing – original draft, Visualization, Validation, Software, Resources, Investigation, Formal analysis, Data curation. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Data curation. **Hang Jiao:** Writing – review & editing, Visualization, Validation, Resources, Investigation, Formal analysis. **Zhong Shuo Chen:** Writing – review & editing, Validation, Investigation, Formal analysis. **Alan J. Murphy:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis. **Zaili Yang:** Writing – review & editing, Visualization, Software, Project administration, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zaili Yang reports financial support was provided by Horizon European Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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