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COVID crisis-aware maritime risk assessment: A Bayesian network analysis

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ABSTRACT

Maritime transportation is a vital component of global trade, yet maritime accidents pose significant risks with far-reaching consequences, including human casualties, economic losses, and environmental damage. The high-risk nature of this sector calls for in-depth, data-driven analysis to enhance risk assessment and accident prevention. While traditional approaches such as probabilistic risk analysis have advanced the understanding of maritime safety, they often overlook the evolving nature of risk under global crises, such as the COVID-19 pandemic (2020), the Ever Given blockage in the Suez Canal (March 2021), ongoing geopolitical conflicts (e.g., Russia-Ukraine since 2022), and the recent Red Sea crisis (2024). To overcome this critical research gap, this study proposes a crisis-aware maritime risk assessment framework based on Bayesian Network (BN), operationalised through a Tree-Augmented Naïve Bayes (TAN) model, using the COVID-19 pandemic as a case study. By analysing maritime accident patterns before and after the pandemic, the model reveals shifts in accident dynamics and emerging risk factors. The BN approach enables objective, interpretable analysis of how underlying causes and safety interventions have evolved in response to the crisis. Additionally, this study indirectly assesses the effectiveness of safety measures implemented during the pandemic and highlights areas for improvement to enhance future resilience. The findings provide actionable insights for policymakers, regulators, and industry stakeholders, supporting the development of more adaptive and robust maritime safety strategies to address future global disruptions.

1. Introduction

Maritime transportation forms the critical infrastructure for global trade and commerce, facilitating the efficient movement of goods across vast oceans [1]. Despite its indispensable role, maritime transport is inherently associated with risks, and accidents may result in severe human casualties and substantial environmental damage. Consequently, ensuring maritime safety at sea and reducing accident risks have always been paramount concerns for the global shipping industry and international regulatory authorities [2].

In recent years, a series of disruptive events have presented unprecedented challenges to maritime safety. The COVID-19 pandemic (2020), the Ever Given blockage in the Suez Canal (March 2021), geopolitical conflicts such as Russia-Ukraine, and the recent Red Sea crisis have not only disrupted global supply chains but also reshaped shipping patterns and altered risk profiles in the maritime industry [3,4]. Disruptions in global supply chains, shifts in shipping patterns, and changes in accident patterns. These "shock events" have demonstrated that crises can trigger both economic disruptions and new safety challenges, underscoring the urgent need to understand their impact on maritime accident trends [5,6].

To capture the full impact of crises on maritime safety, it is essential to examine accident dynamics before and after such events, revealing both direct and indirect consequences. However, this requires comprehensive datasets covering maritime accidents before, during, and after the crisis events, together with robust methods capable of capturing complex interdependencies among risk factors. The COVID-19 pandemic offers a unique opportunity to investigate these dynamics, serving as a case study to examine how global crises can reshape maritime safety conditions and risk evolution [7–9].

Traditional methods, such as probabilistic risk analysis [10], have provided valuable insights into the causes and factors influencing

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maritime accidents [11–13]. However, they often suffer from subjectivity and limited scope, which constrain their ability to fully capture the multifaceted nature of maritime accident risks. In contrast, data-driven approaches, exemplified by the Bayesian Network (BN), offer a more objective and comprehensive understanding of maritime accident risks by leveraging real-world data and probabilistic reasoning [14–17]. Within this family, the Tree Augmented Naïve Bayes (TAN) model provides a powerful extension capable of modelling variable dependencies while maintaining computational efficiency [18–20].

Building on these advancements, this study proposes a novel data-driven BN framework to investigate evolving trends in maritime accidents before and after crisis events, with the COVID-19 pandemic used as an illustrative case. Specifically, the framework integrates accident datasets from the pre-pandemic (2017-2019) and pandemic (2020-2021) periods to: (i) Identify pivotal Risk Influencial Factors (RIFs) shaping maritime accident outcomes; (ii) compare how accident trends and risk profiles shifted across pre- and post-crisis periods; and (iii) evaluate the effectiveness of existing safety measures under changing global conditions. The findings of this study are expected to deepen understanding of the pandemic's long-term effects on maritime safety and contribute to the development of strategies to mitigate the associated risks.

The International Maritime Organization's (IMO) Global Integrated Shipping Information System (GISIS) serves as a crucial repository for maritime accident investigation datasets [21]. However, its direct use is constrained by missing static vessel information. To overcome this limitation, this study supplements GISIS records with static ship attributes obtained from Lloyd's Register Fairplay (LRF) in Information Handling Services (IHS), thereby constructing a comprehensive accident dataset for 2017–2021. Based on this enriched database, a data-driven BN model is developed to examine the impact of the COVID-19 pandemic on maritime accidents.

The specific innovative contributions are as follows:

(1) This paper systematically examines how the COVID-19 pandemic has influenced maritime accident trends by comparing data from pre- and post-pandemic periods, revealing shifts in safety dynamics and risk profiles.
(2) This paper introduces a novel data-driven BN model on real-world maritime accident data to provide an objective assessment of risk. This approach provides a systematic framework for identifying key risk factors and evaluating the effectiveness of current safety measures.
(3) Through the BN model, this paper identifies specific risks associated with the pandemic, such as changes in shipping patterns, regulatory compliance challenges, and new safety concerns, highlighting a deeper understanding of the pandemic's unique impact on maritime safety.

The remainder of this paper is organised as follows. Section 2 reviews the use of BN in maritime risk analysis, revealing the state-of-the-art in the field. Additionally, it evaluates the effects of COVID-19 on shipping and identifies critical gaps in the literature. Section 3 presents a new framework for analysing the impact of the global crisis on maritime accident trends, including creating a novel maritime accident database. This section also details the identification process for RIFs and explains the steps in constructing a data-driven model. The methodology and model verification results are presented in Section 4, providing a comprehensive explanation of the techniques used in the study. Section 5 investigates the changes in maritime accidents before and after the pandemic. By analysing shifts in RIFs from multiple perspectives, it highlights significant trends and dynamics of maritime accident patterns. To conclude, Section 6 summarises the key findings of the study. It further elaborates on the broader implications of these results, emphasising their relevance to future research and practice.

2. Literature review

2.1. A systematic analysis

BN stands out as a powerful probabilistic graphical model with significant advantages in the realm of maritime accident research [22]. A comprehensive retrieval on the Web of Science (WoS), utilising the keywords 'Bayesian network' and 'maritime accident', was conducted, focusing solely on documents indexed in the Science Citation Index Expanded (SCI-Expanded) and Social Sciences Citation Index (SSCI) up to February 2025. This rigorous search yielded a total of 232 relevant documents. The initial content classification of the collected literature indicates a wide range of previous applications of BN in maritime accident analysis. The study of maritime accidents has evolved into a multifaceted field, encompassing a wide range of topics aimed at understanding and mitigating risks associated with maritime operations. Through keyword clustering, the visualisation result is displayed in Fig. 1. The primary research themes can be summarised as follows:

(1) Risk assessment and scenario modelling. Risk assessment remains a cornerstone of maritime safety research [23]. Studies utilise advanced probabilistic tools, such as BNs and their variants, to model accident scenarios and evaluate potential risks [24,25]. Particular focus has been placed on specific contexts, such as ice navigation and oil spill scenarios, where impact scenario models are developed to predict and minimise the consequences of accidents [26].
(2) Human and organisational factors [27]. A significant body of work examines the contribution of human errors and organisational factors to maritime accidents. The Human Factors Analysis and Classification System (HFACS) framework is widely applied to investigate how individual and systemic errors lead to failures [28–30]. This line of research also explores the role of organisational management and maintenance practices in accident prevention.
(3) Collision risk and decision support. Collision risk is a critical topic within the field, particularly in congested maritime routes [31,32]. Research efforts focus on developing decision support systems to assist in collision avoidance and analysing factors such as corrosion and ship manoeuvrability that may exacerbate collision risks [33]. These studies aim to improve real-time decision-making for enhanced operational safety.
(4) Marine transportation systems. Marine transportation systems are explored in terms of their safety and efficiency [34,35]. This includes investigating decision-making processes, inspection protocols, and collision risk management in maritime logistics. Additionally, there is a growing interest in the safety of emerging transportation routes, such as the Northern Sea Route [36], where extreme environmental conditions pose unique challenges.
(5) Formal Safety Assessment (FSA). The adoption of FSA methodologies has become a standard practice for systematic accident analysis and risk evaluation [37]. This approach integrates human error analysis, accident scenario modelling and the identification of risk factors to develop comprehensive safety measures [38].
(6) Development of frameworks and management systems. Research on frameworks for maritime safety [39] emphasises the integration of information systems and decision-making processes [40]. These frameworks aim to enhance the management of maritime accidents and support safety strategies for transportation systems [41]. Applications to specific contexts, such as Arctic shipping and fishery operations, further underscore the practical relevance of these studies [42].
(7) Maritime accident management and response. Maritime accident management encompasses the development of strategies to mitigate the impact of various accidents [43,44]. Decision

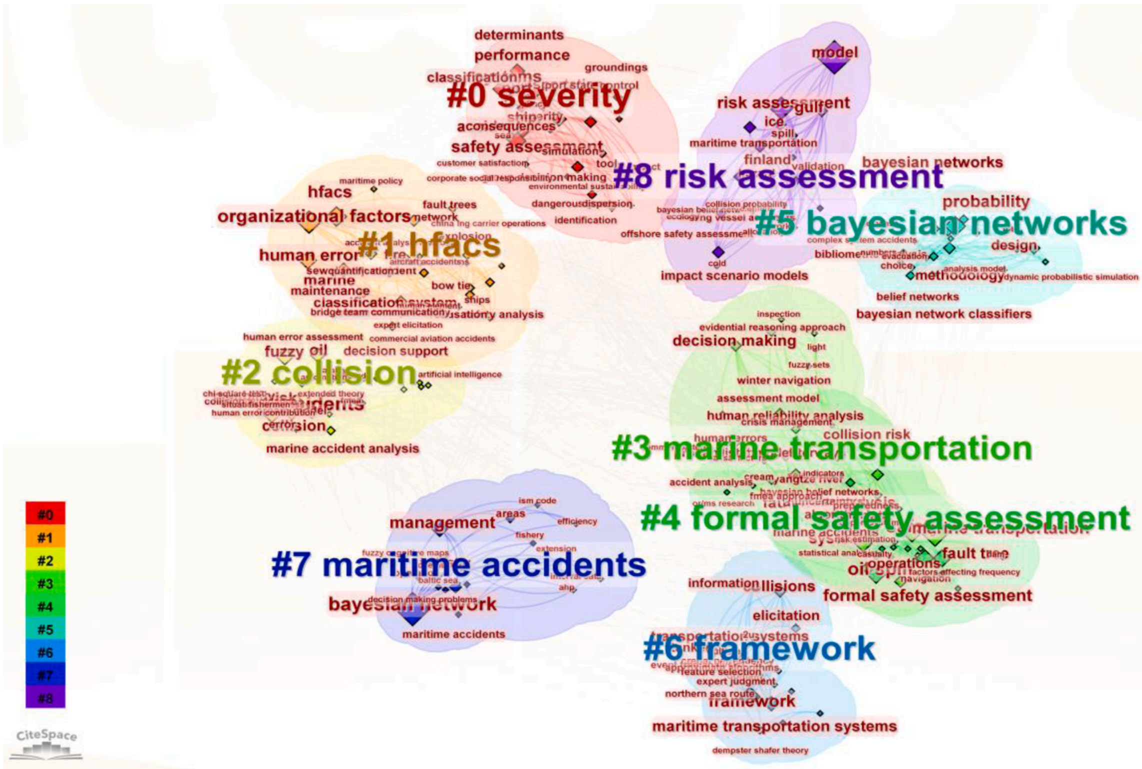

Fig. 1. The clustering analysis of literature keywords in maritime accidents.

support systems are central to this theme, with particular attention given to the safety of fisheries and other critical maritime industries [45]. This research highlights the importance of proactive measures in minimising loss and ensuring sustainability.

(8) Severity and performance evaluation. Accident severity and performance evaluation are key aspects of safety assessment. Studies in this domain focus on identifying determinants of accident severity and analysing their consequences for maritime operations. Groundings and vessel performance are frequently examined to develop better safety protocols and predictive tools [39,46].

In conclusion, maritime accident research encompasses a wide spectrum of challenges, including risk quantification, human factor analysis, and the advancement of decision-support tools and management frameworks. These themes reflect a comprehensive effort to enhance safety, mitigate risks, and improve the overall resilience of maritime operations in both traditional and emerging contexts.

The temporal analysis of research themes in maritime accidents reveals dynamic shifts and emerging trends during the last decade, as shown in Fig. 2. Early studies (2014-2016) primarily focused on foundational topics such as accident severity (#0) and collision risks (#2), which laid the groundwork for understanding maritime safety. As the

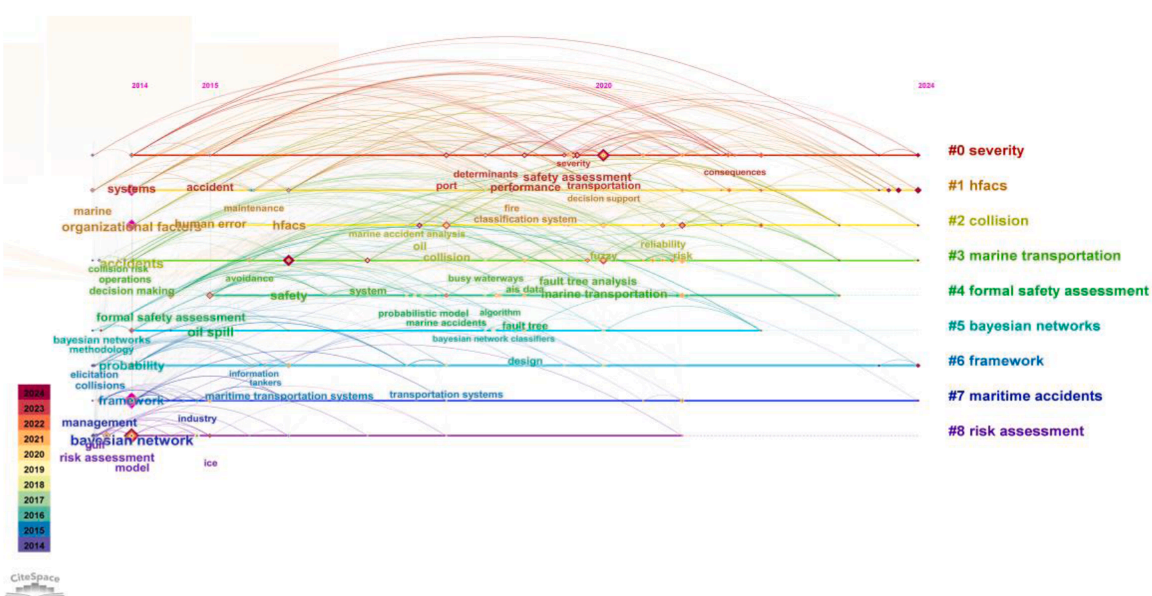

Fig. 2. The temporal analysis of research themes in maritime accidents.

field evolved, research expanded to include decision-making processes (#3) and formal safety assessments (#4), with peak activity occurring between 2018 and 2022. In recent years, there has been a noticeable shift towards data-driven methodologies, particularly the adoption of Bayesian networks (#5) for probabilistic risk modelling and dynamic scenario simulations. Themes such as maritime transportation frameworks (#6) and accident management strategies (#7) have remained consistently relevant, highlighting their central role in addressing practical safety challenges. Furthermore, the increasing emphasis on risk assessment in specific scenarios, such as ice navigation and oil spill mitigation (#8), underscores the growing attention to environmental and situational factors in maritime safety.

This evolution reflects a transition from traditional accident analysis to proactive risk prevention and decision support, driven by technological advancements and the demand for robust management frameworks. It also demonstrates that maritime accident patterns are dynamic over time, influenced by major milestone events. However, to the authors' best knowledge, the impact of global crisis events on maritime accident patterns has not been investigated, despite its crucial role in effective maritime accident management when preparing for future global crises. These insights provide a roadmap for future research, emphasising the integration of cutting-edge techniques with real-world applications to enhance maritime safety and resilience.

2.2. Applications of BN in maritime accidents

Numerous studies have effectively used BN for conducting risk analyses under various specific conditions related to maritime accidents. For instance, Sevgili et al. [47] constructed a data-driven BN based on 2080 accident reports from the US Coast Guard database to predict oil leakage probabilities following tankship accidents. Additionally, Kaptan [48] integrated BN within a fuzzy rule to assess the risk levels of roll-on/roll-off (RORO) ships during the stowage process, providing valuable insights to mitigate operational risks for stakeholders. Ugurlu et al. [49] combined BN with chi-square methods to analyse fishing vessel accidents spanning from 2008 to 2018, revealing significant correlations between accident types and various ship-related parameters. Fan et al. [20] introduced an innovative object-oriented BN framework combined with an enhanced machine-learning approach and mutual information theory to assess maritime risks, identifying key influential factors and non-linear relationships in both traditional accidents and piracy-related incidents, with ship type identified as a major contributor to unsafe conditions.

Further, some studies have focused on specific maritime regions. Zhao et al. [50] employed BN to analyse potential causes of maritime accidents based on over 200 incidents in the Yangtze River waters between 2013 and 2019, suggesting that improved crew retention and autonomous ship development could help reduce accidents. Jiang et al. [51] proposed a BN-based model to evaluate ship stranding probabilities in fluctuating backwater zones, emphasising the temporal and spatial factors that influence accidents in the Three Gorges Reservoir. Additionally, Zhao et al. [52] utilised fuzzy fault tree analysis and BN to assess navigation accident probabilities at Qinzhou Port. Jiang et al. [53] applied a BN-based model to analyse maritime accident risks along the Maritime Silk Road, manually collecting and analysing risk data to identify key influencing factors and conducting scenario analysis for accident prevention insights.

Human factors also play a crucial role in maritime accidents, with BN being used to predict probabilities of unsafe behaviours among seafarers [54], analyse accident reports [55], introduce new human factors analysis frameworks [56], and assess the impact of pilotage on accident probabilities [57]. Moreover, BN has been combined with other techniques to develop accident prevention strategies [58]. Fan et al. [5] introduced a data-driven BN that innovatively integrates human factors into maritime safety analysis, using a TAN to model interdependencies. Validated through sensitivity analysis and historical data, this model reveals critical risk factors and differentiates the impacts of human error across accident types. Wang et al. [59] integrated navigation simulation with Dynamic Bayesian Network (DBN) modelling to assess seafarer-related accident risks, using a collision case study to demonstrate causal pathways through sensitivity analysis.

BN has also been widely used to assess and predict the severity of maritime accidents. For example, Khan et al. [60] employed BN to investigate the handling of dangerous goods in port environments, while Cakir et al. [61] applied BN to oil spill accidents. Similarly, Wang and Yang [62] developed a BN-based method to explore the severity of water traffic accidents, and Zhang et al. [63] conducted a comparative analysis of maritime accident casualties. Wu et al. [64] proposed a new BN method that reduces reliance on expert judgment and demonstrated its reliability through validation with historical navigation accident data.

In summary, BN has proven to be a highly effective tool in maritime accident risk analysis, offering precise insights into accident probabilities and complex interdependencies while adeptly managing uncertainty. Although extensive literature explores the application of BN in various aspects of risk analyses in maritime accidents, there is a noticeable gap in research addressing the impact of global crises such as COVID-19 on maritime accidents. Given the significant disruptions caused by the COVID-19 pandemic on the global shipping and supply chains, it is imperative to comprehensively investigate its influence on maritime accidents in the post-pandemic era. Such research would contribute to developing effective risk management strategies and promoting sustainable growth in maritime transportation. More importantly, it will provide a feasible framework for dealing with the impact of crisis events on maritime accidents in future

2.3. The impact of COVID-19 on maritime transportation

As shown in Table 1, the COVID-19 pandemic substantially affected the maritime transportation sector, disrupting ship operations, port activities, supply chain management, and overall safety. These disruptions have exposed critical vulnerabilities within the industry, particularly in maritime traffic and accident risks, emphasising the urgent need for innovative solutions and adaptive strategies to mitigate these effects and enhance resilience.

Ship operations faced severe challenges due to port restrictions, which hindered crew changes and cargo handling, while prolonged work contracts led to widespread fatigue and mental stress among seafarers [72]. Studies, such as Narasimha et al. [65], revealed substantial reductions in ship traffic and cargo volumes, particularly in Indian seaports. Wang et al. [66] addressed post-pandemic challenges by developing a trajectory recognition and classification model to manage

Table 1
The impact of COVID-19 on research on maritime accidents.

Impact area	Specific impacts	Research and solutions
Ship Operations	¨ Port restrictions hindered crew changes and cargo handling. ¨ Prolonged work contracts caused fatigue and mental stress.	¨ Highlighted reduced traffic and cargo volumes in Indian ports [65]. ¨ Developed models to manage increased port traffic and docking times [66].
Port Operations	¨ Lockdowns disrupted goods flow and reduced port capacity. ¨ Global maritime connectivity declined.	¨ Created resilience models for port operations [67]. ¨ Examined connectivity drops due to restrictions [68].
Supply Chain Management	¨ Demand for medical supplies surged, while oil demand dropped. ¨ JIT supply chains faced severe backlogs.	¨ Built models to assess demand shifts [69]. ¨ Used AIS data for port clustering and monitoring [70].
Safety Concerns	¨ Fatigue and delays increased accident risks.	¨ Proposed tools to improve accident prevention in pandemic contexts [71].

increased port traffic and docking times, noting a rise in daily berth utilisation for cargo ships and oil tankers.

Port operations were also significantly affected, with lockdowns disrupting the flow of goods and reducing port capacity. Global maritime connectivity declined as a result of these restrictions [73]. Panahi et al. [67] developed a resilience assessment model to support sustainable port operations during the uncertainties brought on by COVID-19, while Guerrero et al. [68] examined connectivity drops and their regional impacts, revealing variations based on government-imposed mitigation measures.

Supply chain management in the maritime sector experienced profound disruptions [65]. A surge in demand for medical supplies coincided with a sharp drop in oil demand, placing immense pressure on Just-in-Time (JIT) supply chains, which struggled with severe backlogs and bottlenecks [71]. As COVID-19 restrictions begin to ease and demands recover, the maritime transportation system is tested further in its ability to adapt to changing market conditions [74–76]. Zhao et al. [69] examined changes in dry bulk and container transport by employing the China Coastal Bulk Freight Index (CCBFI) and the Baltic Dry Index (BDI) as key indicators, and developed models to capture the external impacts of COVID-19 on the shipping industry. Zheng et al. [70] developed a port classification model based on Automatic Identification System (AIS) data to monitor and predict ship behaviour, highlighting the effectiveness of port clustering methods in tracking maritime transmission paths during the pandemic.

In addition to operational challenges, the pandemic increased safety risks in the maritime sector. Fatigue and delays contributed to higher accident risks, prompting researchers to propose tools for accident prevention in pandemic contexts. These efforts aim to improve safety measures and ensure the resilience of maritime operations in the face of future disruptions.

As the maritime industry recovers, it must continue to adapt to the evolving challenges introduced by the pandemic. This study aims to provide a comprehensive and academically precise analysis of these impacts, with a particular focus on maritime traffic and accident risks. The industry can enhance its resilience, sustainability, and safety by addressing these challenges in a post-pandemic world.

2.4. Research gaps

The extensive literature review identifies several critical research gaps in maritime accident analysis that require further investigation:

(1) Lack of methodologies for quantifying the impact of global crises on maritime accidents.

Existing research lacks comprehensive methodologies to systematically assess how various global crises, including economic downturns, geopolitical conflicts, pandemics, and natural disasters, influence maritime accident patterns. While the COVID-19 pandemic serves as a relevant case study due to its widespread disruptions, a broader framework is needed to evaluate the effects of different crisis events on accident rates, types, and severity. Developing such methodologies is crucial for improving risk assessment and enhancing crisis preparedness in the maritime sector.

(2) Deficiencies in maritime accident databases and reporting during global crises.

Disruptions caused by global crises may compromise the completeness, consistency, and accuracy of maritime accident data. Inadequate reporting and data loss during such periods hinder the ability to conduct thorough analyses of accident trends and risks. Enhancing maritime accident databases and reporting systems to account for data inconsistencies and gaps during crisis events is essential for enabling reliable risk assessment and accident prevention strategies.

(3) Insufficient integration of global crisis factors in maritime accident risk assessment models.

Current maritime accident risk assessment models often fail to incorporate emergent crisis-related factors, such as port congestion, workforce shortages, and disruptions in global supply chains. These factors, which arise during crises like geopolitical conflicts, pandemics, or financial crises, significantly impact navigational safety but remain underrepresented in existing models. Incorporating crisis-induced variables into accident risk assessment frameworks will enhance their predictive accuracy and real-world applicability.

To address these gaps, this study develops a data-driven BN framework using a TAN model to systematically analyse the impact of global crises on maritime accidents. While COVID-19 serves as a case study due to its extensive data availability, the proposed methodology is designed to be adaptable to other crisis events, providing broader insights into maritime accident dynamics and contributing to more effective risk management and policy development.

3. Methodology

3.1. The proposed framework

This study employs a data-driven BN model to examine the impact of global crises on maritime accidents, using COVID-19 as a case study. The methodological framework is illustrated in Fig. 3. Maritime accident records and incident reports from 2017 to 2021 were collected from the IMO GISIS. To address gaps in static vessel data, additional information was integrated from the IHS-LRF database.

The dataset was then divided into two distinct periods: 2017–2019 (pre-pandemic) and 2020–2021 (during the pandemic). The pre-pandemic period serves as a baseline to represent the normal maritime accident pattern before the occurrence of COVID-19, while the latter period captures changes in accident trends during the pandemic. Moving forward, GISIS data from 2022 to 2025 will continue to be collected to analyse post-pandemic trends once it becomes available. However, the currently available 2017–2021 data is sufficient to support the primary objective of this study, developing a new framework for analysing the impact of global crises on maritime accident pattern shifts.

A total of 24 RIFs were identified based on prior literature and IMO standards, with precise definitions established for each RIF status. Using these datasets and RIFs, separate data-driven BN models were developed to assess maritime accident patterns before and after COVID-19 [6]. This approach provides a systematic method for evaluating how global crises impact maritime safety, enabling more effective risk management and policy development.

Model validation was conducted through sensitivity analysis, confusion matrix evaluation, axiom testing, and kappa coefficient calculation [6]. Finally, a comparative analysis of maritime accidents between the two periods highlights the evolving accident characteristics in response to the COVID-19 pandemic.

3.2. Dataset collection and generation

To build a reliable dataset for this study, maritime accident information between 2017 and 2021 was compiled primarily from the IMO GISIS and the IHS-LRF databases. The GISIS casualty module provides structured records of maritime casualties and incidents reported in compliance with IMO requirements. These records contain essential attributes such as accident time and location, vessel identity, and a brief description of causes. In addition, some cases are accompanied by full investigation reports, which provide richer details including ship navigational status, prevailing environmental conditions, accident progression, and causal analysis.

Since the GISIS database often lacks complete ship-specific information (e.g., vessel age, hull construction, hull material, and type), static ship data from the IHS-LRF database were used to supplement missing attributes. Cross-referencing was performed using each vessel's IMO number and Maritime Mobile Service Identity (MMSI) to merge the two sources, ensuring consistency and reliability of the integrated dataset.

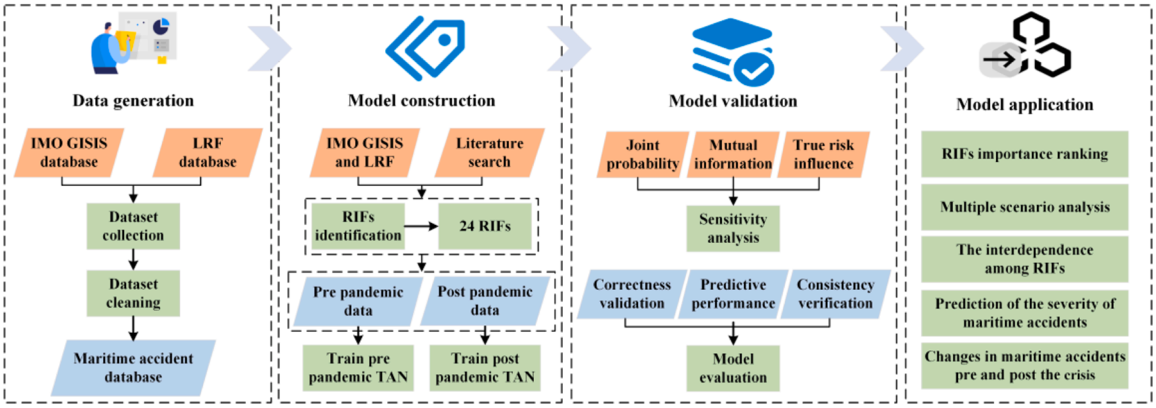

Fig. 3. The framework diagram of this paper.

The raw accident dataset was initially extracted from GISIS, covering 1105 accident reports recorded between 1 January 2017 and 31 December 2021. The subsequent data refinement process followed three major steps:

(1) Data cleansing: Accidents involving fishing vessels were removed due to extremely limited information, where only static vessel data were available in many cases. These records could not be enriched with external sources to support the 23 RIFs required for this study. Similarly, incidents involving domestic ferries and naval ships were excluded, as they often lacked usable details. After this stage, 462 accident records remained.
(2) Data completion: For the retained records, the IHS-LRF database was used to fill in missing static vessel attributes such as hull material, hull type, vessel age, length, breadth, deadweight, and gross tonnage. By systematically matching IMO numbers and MMSI identifiers, data gaps were minimised and internal consistency was maintained. Following this step, 428 accident records contained complete information relevant to all identified RIFs.
(3) Data screening: A double check was conducted on the supplemented dataset to validate accuracy and relevance. Records were excluded if they lacked adequate causal explanations, ship equipment details, or environmental conditions necessary for risk analysis. After this screening, a total of 402 high-quality accident records were retained as the final dataset for subsequent modelling and analysis.

This integrated database provides a solid and robust foundation for the study, enabling an in-depth analysis of maritime accidents during the COVID-19 pandemic. Beyond the immediate scope of this research, the database serves as a valuable resource for future maritime safety studies, offering insights into the complex dynamics of maritime operations during global crises.

3.3. RIF identification

Accurate identification of RIFs is pivotal for precisely pinpointing the potential causes and sources of risk in maritime accidents. In this study, RIF identification was guided by the IMO classification framework and supported by an extensive review of relevant literature [6,8,77] and IMO accident reports. RIFs with higher occurrence frequencies were carefully screened, leading to the selection of 24 key RIFs spanning accident-related, ship-related, environmental, navigational, and human factors. This refined dataset enables a systematic examination of how COVID-19 has influenced maritime accidents across multiple RIFs.

Following RIF identification, the detailed definition of RIF status facilitates quantitative analysis and standardisation of maritime accidents. Previous studies often simplified RIF status definitions to streamline quantitative modelling, but this reduced analytical precision [77] and limited the applicability of results. Recognising the multifaceted impact of COVID-19, this paper adopts a detailed approach that defines the statuses of the identified RIFs within the maritime transportation context. For instance, the voyage segment classification provided by the IMO is utilised, including eight distinct geographical regions. Furthermore, the 'ship type' category has been expanded to incorporate offshore vessels, categories that have been neglected in prior studies, thereby ensuring a more thorough analysis. Ultimately, all recognised RIFs and their respective status descriptions are graphically represented in Fig. 4.

3.4. Model construction

The dataset was split into pre-pandemic (2017–2019) and pandemic (2020-2021) periods, with separate TAN models constructed to allow comparative analysis of COVID-19′s impact on maritime accidents. The TAN model was selected due to its ability to account for dependencies among variables, offering distinct advantages over Naïve Bayes Network (NBN) and Augmented Bayes Network (ABN) models. Unlike NBN, which assumes conditional independence among variables, TAN accommodates inter-variable dependencies during structure construction, providing a more realistic representation of the relationships between RIFs in maritime accidents. Compared with ABN, TAN also achieves a balance between model flexibility and computational efficiency by introducing a tree-based structure, in which each attribute is linked to the class variable and at most one other attribute. This approach enhances interpretability and scalability, making it particularly suitable for handling high-dimensional maritime accident data.

The construction of a TAN model begins with structure learning, which specifies variable dependencies through a Directed Acyclic Graph (DAG) [5,13]. Structure learning can generally be achieved using expert-driven approaches, data-driven techniques, or a combination of both. In this study, a data-driven strategy was applied, with TAN chosen as the learning algorithm. The task of TAN structure learning can be expressed as an optimisation problem: identifying a tree structure across the attribute variables that maximises the data log-likelihood while remaining consistent with the designated class variable [78,79]. To address this, the study employed the 'Construct-TAN' algorithm introduced by Friedman et al. [80], which utilises conditional mutual information to evaluate interdependencies among attribute variables, defined as follows:

$$I_P(X_i, X_j|C) = \sum_{x_{ii}, x_{ji}, c_i} P(x_{ii}, x_{ji}, c_i) \log \frac{P(x_{ii}, x_{ji}|c_i)}{P(x_{ii}|c_i) P(x_{ji}|c_i)} \tag{1}$$

Here, I_P denotes the conditional mutual information, x_{ii} refers to the ith state of the attribute variable X_i, x_{ji} represents the ith state of the

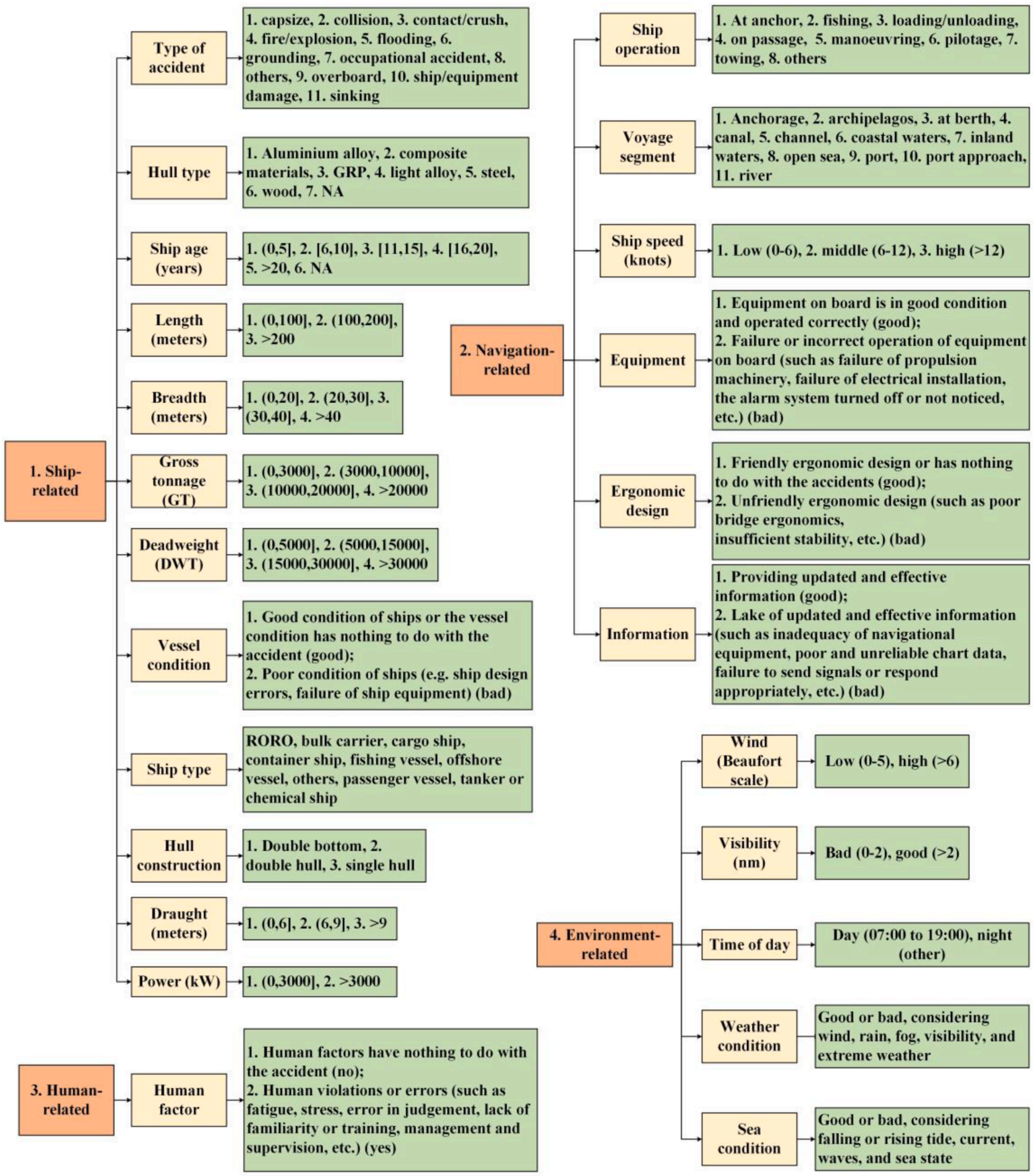

Fig. 4. The details of RIFs and states.

attribute variable X_j, and c_i corresponds to the ith state of the class variable C. Based on this measure, TAN builds a maximum-weight spanning tree to capture the strongest inter-variable dependencies.

Once the qualitative structure of the TAN network is established, parameter learning is required to determine the conditional probability distribution of each node. For complete datasets, Bayesian Estimation is preferred over Maximum Likelihood Estimation because it provides more stable and accurate probability estimates, particularly in cases with relatively small sample sizes. This step ensures that the constructed network not only has a logically consistent structure but also captures the statistical characteristics of the observed data.

The final step is to apply the model to risk analysis. The constructed TAN models for the two time periods were used to conduct both qualitative and quantitative analyses. First, the models qualitatively examined changes in RIFs and their interdependencies before and during COVID-19. Second, quantitative assessments were carried out, including marginal probability estimation of targeted RIFs and the ranking of RIFs based on their contributions to maritime accidents.

In summary, TAN integrates the strengths of BN and decision trees, offering a versatile, interpretable, and statistically robust framework for risk modelling. The two models constructed for the pre-pandemic and pandemic periods provide a systematic means of examining how maritime accident risk factors evolved under the influence of COVID-19.

4. Model validation

4.1. Sensitivity analysis

Sensitivity analysis is essential for addressing uncertainty in maritime safety, as it identifies how key factors influence critical outcomes. This study applies an integrated approach that combines mutual information, joint probability distributions and the True Risk Influence (TRI) method to capture variable interdependencies, assess their relative importance and quantify their impact on accident risk. This multi-method design enhances both the robustness and reliability of the analysis.

4.1.1. Mutual information

Mutual information is a statistical metric that quantifies the dependency between two variables by measuring how much knowledge of one reduces uncertainty about the other. Larger values indicate stronger associations and greater predictive power. In sensitivity analysis, it is commonly applied to gauge the influence of individual variables on a target outcome, thereby highlighting the most critical factors within a system.

Within the TAN model, the parent node ‘Type of casualty’ is linked to 24 RIFs as child nodes. Mutual Information Value and Variance of Beliefs are computed separately for COVID-19 and the ‘Type of casualty’ node across two periods: pre-COVID-19 (2017-2019) and post-COVID-19 (2020-2021). The results are presented in Fig. 5 and Fig. 6, respectively. RIFs with mutual information values exceeding the average are identified as having a significant impact on accident severity.

The findings reveal a shift in the key factors influencing accident severity before and after COVID-19:

Pre-COVID-19 (2017–2019): The most influential factors were ‘Type of accident’ (0.2564), ‘Ship operation’ (0.1081), ‘Ship type’ (0.0882), ‘Voyage segment’ (0.0747), and ‘Hull type’ (0.0461).

Post-COVID-19 (2020–2021): The critical factors included ‘Type of accident’ (0.3582), ‘Ship type’ (0.1376), ‘Ship operation’ (0.0908), ‘Voyage segment’ (0.0858), ‘Ship age’ (0.0715), ‘Breadth’ (0.0556), and ‘Deadweight’ (0.0506).

These findings suggest that the maritime industry may have experienced structural changes or operational adjustments during the pandemic, leading to shifts in the determinants of accident severity. Furthermore, the increased weighting of accident types post-COVID-19 indicates that certain types of accidents became more frequent or severe, underscoring the evolving nature of maritime risks in response to global disruptions.

These insights also prompt further studies to conduct a deeper root-cause analysis of these changes. Understanding why certain types of accidents have increased in frequency and severity is crucial and warrants further investigation, providing valuable guidance for shaping future research agendas in the field. Additionally, scientific evidence on the impact of reduced crew activities, including restricted social interactions, prolonged isolation, and psychological stress in maritime work environments, should be further explored as part of the future research agenda to better assess their role in maritime accident trends.

4.1.2. Joint probability distribution

Mutual information analysis identified key RIFs across two distinct periods. Building on these findings, joint probability distributions were applied to assess how different states and variables influence accident severity. To preserve the integrity of probability distributions within the BN framework, normalisation conditions were enforced. This step ensures the accurate computation of posterior probabilities for any given variable and improves the efficiency of Bayesian inference.

To analyse the impact of each RIF state individually, a probability of 100 % was assigned to each state, generating joint probability outcomes. Results from 2017 to 2019 (pre-pandemic) are shown in Table 2, and those from 2020 to 2021 (post-pandemic) are shown in Table 3. The calculation results reveal how different RIF states influence accident severity, classified into three casualty levels. The most impactful states for each RIF are highlighted in bold, while the least impactful states are underlined. The first row of each table presents the baseline probabilities before any RIF state adjustments. Subsequent rows show how casualty probabilities change when a specific RIF is fixed in a given state.

During the pre-pandemic period, accident severity varied significantly across different accident types. Occupational accidents had the highest probability (96.588 %) of leading to severe casualties, whereas contact/crush accidents had the lowest (22.195 %).

The ship operation phase also played a crucial role in accident severity. The loading/unloading phase exhibited the highest likelihood of serious accidents (85.97 %), while the pilot stage had the lowest (20.472 %), indicating that certain operational activities posed greater risks.

Among different vessel types, fishing boats had the highest probability of serious accidents (86 %), whereas RORO ships experienced the lowest (20.618 %). This suggests that vessel design and operational characteristics significantly influenced accident outcomes.

Accidents in different voyage segments also showed varying degrees of severity. Incidents occurring in berths had the highest probability of severe casualties (87.363 %), whereas accidents in canal areas had the lowest (14.872 %). This trend highlights how location-specific factors affect accident risks.

Finally, hull type emerged as another key determinant of accident severity. Wooden ships were most vulnerable, with an 87.065 % probability of severe casualties, while light alloy hulls had the lowest (13.109 %), underscoring the importance of ship material in accident resilience.

In the post-pandemic period, significant shifts were observed in accident probability distributions, particularly in open waters, suggesting changing risk patterns in maritime operations. Notably, fishing vessels exhibited a heightened likelihood of severe accidents, reflecting evolving industry challenges and vulnerabilities.

These findings suggest that structural and operational adjustments in the maritime sector during the pandemic may have had a significant

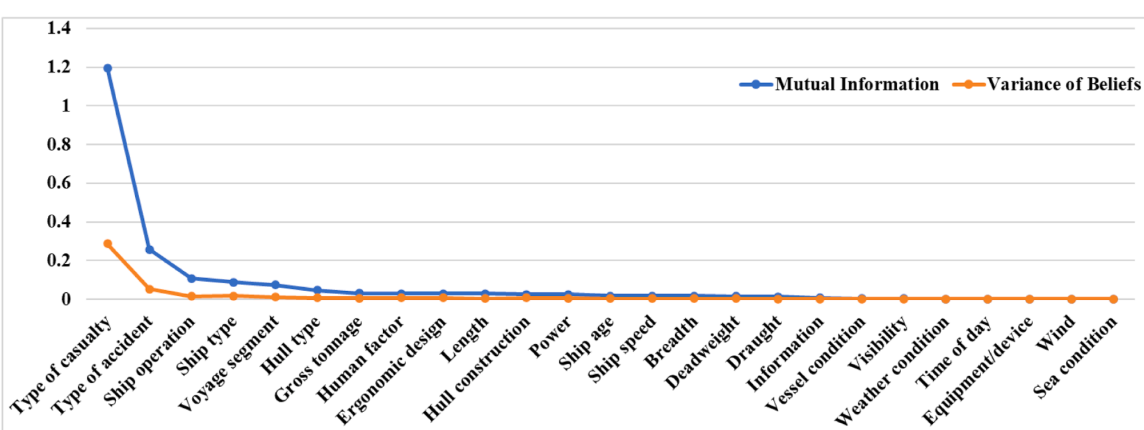

Fig. 5. Visualisation of different results between ‘Type of casualty’ and RIFs pre-COVID-19.

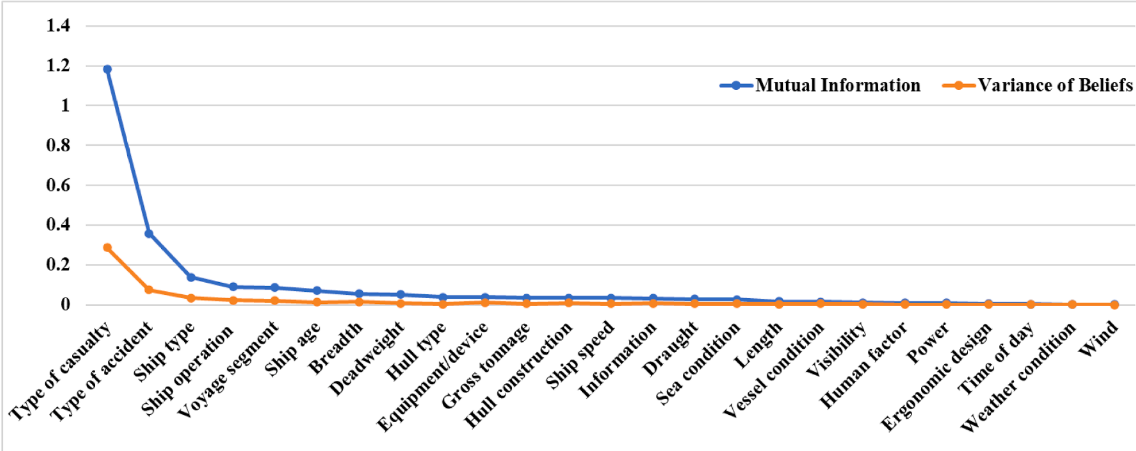

Fig. 6. Visualisation of different results between 'Type of casualty' and RIFs after COVID-19.

impact on accident severity. The heightened risks associated with specific accident types and vessel categories underscore the urgent need for adaptive risk mitigation strategies to address evolving maritime safety challenges. Moreover, these insights provide valuable perspectives for further exploration, particularly in understanding why certain countries or regions managed the COVID-19 pandemic more effectively than others. They also offer a foundation for investigating how these findings can inform assessments of the effectiveness of decisions made by different countries and companies in managing COVID-19 and mitigating its impact on ship safety.

4.1.3. True risk influence

The TRI method, pioneered by [81], stands as a robust tool for assessing multivariate sensitivity, finding extensive application within maritime safety research. Given the multitude of states inherent in the risk factors under consideration (RIF), this study adopts the TRI methodology to gauge the influence of each key risk factor on accident severity. The TRI value offers a comprehensive insight into the magnitude of each risk factor's impact [77,79]. The specific calculation formula is as follows.

$$TRI = \frac{|P_0 - P_{\min}| + |P_0 - P_{\max}|}{2}. \quad (2)$$

where P_0 is the baseline probability of the target node (e.g., type of casualty) given the current BN without intervention. $P_{\max}$ indicates the maximum conditional probability of the target node when a risk factor (RIF) is forced into the state that has the strongest effect. $P_{\min}$ denotes the minimum conditional probability of the target node when the same RIF is forced into the state that has the weakest effect.

$P_{\max}$ and $P_{\min}$ are calculated by systematically forcing each possible state of a risk factor to 100 % in the BN and recording the resulting probability of the target variable. The maximum probability value ($P_{\max}$) is highlighted in bold, while the minimum probability value ($P_{\min}$) is underlined in Table 2 and Table 3 in the two periods, respectively. The TRI calculation results and ranking of all RIFs in the two periods are shown in Table 4 and Table 5. It can be clearly seen from the results that 'Type of accident' is always the biggest factor affecting 'Type of casualty'. Moreover, the same RIF has different effects on accidents of different severity. The TRI analysis reveals critical insights for maritime safety management. The consistent influence of 'Type of accident' on casualty severity highlights the need for targeted safety measures tailored to specific accident types. Additionally, the shift in risk factor rankings pre- and post-COVID-19 underscores the importance of adaptive risk management strategies that account for changing global conditions. These findings emphasise the necessity for dynamic and context-specific safety frameworks to enhance maritime resilience and reduce accident severity.

The key implications for maritime safety management derived from the above findings are listed below.

(1) Targeted safety measures for specific accident types.

The consistent influence of 'Type of accident' on casualty severity underscores the necessity for accident-specific safety interventions. Maritime authorities and companies should develop tailored risk mitigation strategies based on high-risk accident types to minimise severe casualties and enhance overall safety resilience.

(2) Adapting risk management to changing global conditions.

The shift in RIF rankings pre- and post-COVID-19 highlights how external disruptions can alter maritime risk dynamics. For instance, 'Ship type' rose in importance post-pandemic, suggesting that different vessel categories faced heightened risks due to operational or regulatory changes. This finding underscores the importance of adaptive risk management frameworks that can respond to evolving maritime challenges, including pandemics, economic downturns, and geopolitical disruptions.

(3) Understanding structural and operational adjustments in maritime transport.

The variations in RIF rankings suggest that structural and/or operational adjustments in the maritime industry during the pandemic influenced accident severity. These changes suggest solutions relating to altered shipping routes, reduced crew availability, new regulatory constraints, or economic pressures affecting maintenance schedules and vessel operations. Understanding these shifts can guide policy refinements and industry best practices to prevent future risks under similar crisis scenarios.

(4) Future research and policy development for maritime resilience.

These findings highlight the need for continuous monitoring of accident patterns to inform evidence-based policymaking. The results also prompt further investigations into why certain risk factors became more significant post-pandemic and how different maritime policies and operational strategies contributed to varying safety outcomes across regions. Future research should explore the long-term impacts of global crises on maritime safety and evaluate whether regulatory interventions implemented during the pandemic had a lasting effect on risk reduction.

(5) Broader implications for global crisis preparedness.

The observed shifts in maritime risk factors during the pandemic can inform broader crisis preparedness strategies. The maritime sector must develop flexible safety policies that can quickly adapt to disruptions, ensuring resilience against future global crises. Additionally, enhanced data-driven risk assessment frameworks should be established to provide real-time insights into accident trends, enabling proactive safety measures rather than reactive responses.

Table 2
The joint probability of each variable and accident severity pre-COVID-19.

original	less serious 8.034	serious 26.119	very serious 65.846
Type of accident			
capsize	0.435	4.902	94.664
collision	10.433	33.294	56.273
contact/crush	**34.149**	43.656	22.195
fire/explosion	6.971	41.730	51.299
flooding	2.945	33.214	63.841
grounding	10.566	**48.129**	41.305
occupational accident	1.685	1.727	**96.588**
others	1.542	33.199	65.259
overboard	3.641	0.339	96.019
ship/equipment damage	9.488	45.102	45.410
sinking	0.634	7.146	92.221
Ship operation			
at anchor	2.276	25.190	72.534
fishing	8.957	22.075	68.969
loading/unloading	7.721	6.309	**85.970**
manoeuvring	15.383	42.104	42.513
on passage	3.864	23.997	72.139
others	13.846	17.473	68.681
pilotage	**32.220**	**47.308**	20.472
towing	16.683	10.748	72.569
Ship type			
RORO	11.483	**67.898**	20.618
bulk carrier	5.887	29.497	64.616
cargo ship	8.648	20.645	70.707
container ship	4.213	27.322	68.465
dredger	8.481	12.230	79.288
fishing vessel	2.797	11.203	**86.000**
offshore vessels	17.682	36.471	45.847
others	14.186	17.169	68.645
passenger vessel	**22.449**	33.348	44.203
tanker or chemical ship	4.621	27.266	68.113
tug	10.758	5.857	83.384
Voyage segment			
Inland waters	22.979	12.391	64.63
anchorage	2.039	25.554	72.407
archipelagos	11.829	31.057	57.114
at berth	2.960	9.677	**87.363**
canal	**46.042**	**39.086**	14.872
channel	32.007	39.038	28.956
coastal waters	3.607	30.498	65.896
open sea	4.230	19.602	76.168
port	10.468	29.265	60.267
port approach	21.697	32.077	46.226
river	4.415	29.444	66.141
Hull type			
GRP	7.193	8.881	83.926
NA	8.745	29.879	61.376
aluminium alloy	17.620	**59.861**	22.520
composite materials	17.506	39.608	42.887
light alloy	**27.435**	59.455	13.109
steel	7.274	25.913	66.812
wood	5.788	7.146	**87.065**

Table 3
The joint probability of each variable and accident severity post-COVID-19.

original	less serious 4.747	serious 35.375	very serious 59.877
Type of accident			
capsize	3.481	4.323	92.196
collision	0.602	53.082	46.316
contact/crush	**34.343**	22.341	43.316
fire/explosion	0.967	61.233	37.800
grounding	0.865	**76.236**	22.900
occupational accident	0.958	1.189	**97.853**
others	1.511	39.408	59.081
overboard	9.615	1.085	89.300
ship/equipment damage	2.430	33.200	64.370
sinking	2.419	3.004	94.577
Ship type			
RORO	7.400	58.597	34.003
bulk carrier	1.261	29.258	69.48
cargo ship	5.240	38.101	56.659
container ship	2.732	**84.716**	12.552
fishing vessel	1.649	21.453	76.898
offshore vessels	3.957	24.163	71.880
others	5.335	15.078	**79.588**
passenger vessel	**36.705**	24.105	39.190
tanker or chemical ship	6.226	32.710	61.064
Ship operation			
at anchor	2.440	27.074	70.486
fishing	4.621	11.027	**84.352**
loading/unloading	8.224	19.627	72.149
manoeuvring	**19.817**	38.178	42.006
on passage	3.718	35.523	60.758
pilotage	3.675	**72.223**	24.102
Voyage segment			
Inland waters	7.686	20.911	71.403
anchorage	3.716	27.297	68.987
archipelagos	5.619	42.187	52.195
coastal waters	8.593	38.672	52.735
open sea	**0.845**	22.127	**77.028**
port	8.434	48.956	42.610
port approach	3.729	**63.712**	32.558
river	3.875	41.554	54.570
Ship age			
1	2.847	30.394	66.759
2	1.692	23.893	74.414
3	**13.02**	37.518	49.465
4	8.357	31.807	59.835
5	1.111	**50.350**	48.539
6	5.198	12.845	**81.957**
Breadth			
1	5.310	30.399	64.291
2	7.055	**46.426**	46.520
3	2.554	14.198	**83.248**
4	**1.975**	52.901	45.124
Deadweight			
1	4.085	30.619	65.296
2	**12.907**	**49.340**	37.754
4	1.300	33.030	**65.670**

4.2. Model correctness verification

To enhance the robustness of the BN-based model, this study conducts a sensitivity analysis to validate its accuracy. This analysis adheres to two fundamental axioms:

Axiom 1: Minor adjustments in the prior probabilities of each RIF should correspondingly influence the posterior probability of the target node. This axiom ensures that even slight changes in the input variables lead to proportional changes in the output, reflecting the model's responsiveness to variations in RIF probabilities.

Axiom 2: The total impact of integrating the probability variations of x parameters should be larger than the one from the set of $y(y \in x)$ RIFs.

Adherence to these axioms during the sensitivity analysis serves to validate the model's reliability and ensure its consistency in reflecting the intricate relationships among the RIFs and the target node. To validate the model's compliance with the two axioms, the collective impact of all filtered significant RIFs on casualty types is examined. The parent node 'casualty type' remains constant, and the variations of each type are individually investigated. Using 'very serious' accidents as an example, 'type of accident' is designated as the initial node, with its prior probability incremented by 2 % to reach the extreme states that exert the greatest and least influence on 'lighter' accidents. This process is repeated for other RIFs. The sequence presented in the first column of Table 6 and Table 7 depicts the cumulative probability change values. Subsequently, the process is repeated for the remaining two casualty types, yielding the computation outcomes illustrated in the subsequent columns of Table 6 and Table 7.

The second column of Table 6 and Table 7 displays the original probability values for each casualty type in the TAN structure, while the subsequent columns exhibit the updated cumulative change values. The findings indicate that adjustments in the prior probability of a selected RIF correlate with corresponding variations in the posterior probability

Table 4
TRI of important RIFs for three types of casualty (100 %) pre-COVID-19.

Node	less serious		serious		very serious		**Average**
	TRI	Rank	TRI	Rank	TRI	Rank	
Type of accident	16.857	2	23.895	3	37.197	1	**25.983**
Ship operation	14.972	3	20.499	4	32.749	4	**22.740**
Ship type	9.826	5	31.020	1	32.691	5	**24.512**
Voyage segment	22.002	1	14.704	5	36.245	3	**24.317**
Hull type	10.823	4	26.357	2	36.978	2	**24.719**

Table 5
TRI of important RIFs for three types of casualty (100 %) post-COVID-19.

Node	less serious		serious		very serious		**Average**
	TRI	Rank	TRI	Rank	TRI	Rank	TRI
Type of accident	16.871	2	37.575	1	37.4765	1	**30.641**
Ship type	17.722	1	34.819	2	33.518	2	**28.686**
Ship operation	8.689	3	30.598	3	30.125	3	**23.137**
Voyage segment	3.874	6	21.401	4	22.235	4	**15.836**
Ship age	5.953	4	18.753	5	16.709	6	**13.805**
Breadth	2.540	7	16.114	6	19.062	5	**12.572**
Deadweight	5.803	5	9.361	7	13.958	7	**9.707**

Table 6
The combined influence of multiple variables before COVID-19.

Type of accident		+2 %	+2 %	+2 %	+2 %	+2 %
Ship operation			+2 %	+2 %	+2 %	+2 %
Ship type				+2 %	+2 %	+2 %
Voyage segment					+2 %	+2 %
Hull type						+2 %
less serious	8.034	8.709	9.326	9.791	10.720	11.145
serious	26.119	27.075	27.905	29.154	29.709	30.819
very serious	65.846	67.334	68.648	69.947	71.087	72.584

of the respective casualty type, thereby validating Axiom 1. Moreover, the cumulative probability change value of the parent node escalates sequentially as the number of altered variables increases, as evidenced by the collective values across all columns, affirming Axiom 2. Consequently, these results substantiate the accuracy of the model.

4.3. Prediction performance verification

This study employed a training-testing split to evaluate predictive performance. A hold-out validation strategy was applied, in which 80 % of the accident records (322 cases) were randomly allocated to the training set for model development, and the remaining 20 % (80 cases) were reserved as an independent test set for performance assessment. This separation of training and testing data helps to mitigate the risk of overfitting. To further ensure robustness, the random split was repeated multiple times during preliminary experiments, confirming that the results were consistent and not overly sensitive to a particular partition of the data.

Similar to mainstream classification research, this study employs accuracy as a metric to assess the overall performance of the model on the test set. Additionally, it utilises the confusion matrix along with several related indicators, including precision, recall, F-measure, specificity, False Positive Rate (FPR), and area under the ROC curve (AUC), to evaluate the classification effectiveness of the model for each subclass.

Precision, representing the ratio of correctly predicted positive samples to all samples predicted as positive by the classifier, and recall, denoting the proportion of correctly predicted positive samples to the actual positive class samples, are crucial in assessing classification accuracy and consistency. F-measure, serving as the harmonic mean of precision and recall, offers a comprehensive evaluation of the model's performance. Specificity gauges the model's aptitude in accurately categorising negative samples, while FPR quantifies the extent to which the model misclassifies negative samples as positive. AUC, encompassing the overall model performance across various thresholds, provides a comprehensive evaluation. The confusion matrix depicting the model's prediction results is presented in Fig. 7, with the corresponding calculation outcomes of each indicator delineated in Table 8.

4.4. Model consistency verification

The marine accident data set used in this study has obvious problems of uneven class distribution. The 'very serious' type accounted for 64.9 % of accident severity, while the 'less serious' type accounted for only 7.48 %. Therefore, the Kappa coefficient is introduced to test the consistency of the model in predicting the severity of various accidents [54].

The calculated result of the Kappa coefficient is usually between [0,1]. The larger the value, the more correct the classification result is. When the kappa value falls within the range of [0.81,1], it can be

Table 7
The combined influence of multiple variables after COVID-19.

Type of accident		+2 %	+2 %	+2 %	+2 %	+2 %	+2 %	+2 %
Ship type			+2 %	+2 %	+2 %	+2 %	+2 %	+2 %
Ship operation				+2 %	+2 %	+2 %	+2 %	+2 %
Voyage segment					+2 %	+2 %	+2 %	+2 %
Ship age						+2 %	+2 %	+2 %
Breadth							+2 %	+2 %
Deadweight								+2 %
less serious	4.747	5.422	6.221	6.675	6.881	7.214	7.351	7.643
serious	35.375	36.111	37.503	38.747	39.67	40.493	41.187	41.588
very serious	59.877	61.377	62.712	63.897	64.779	65.371	66.06	66.657

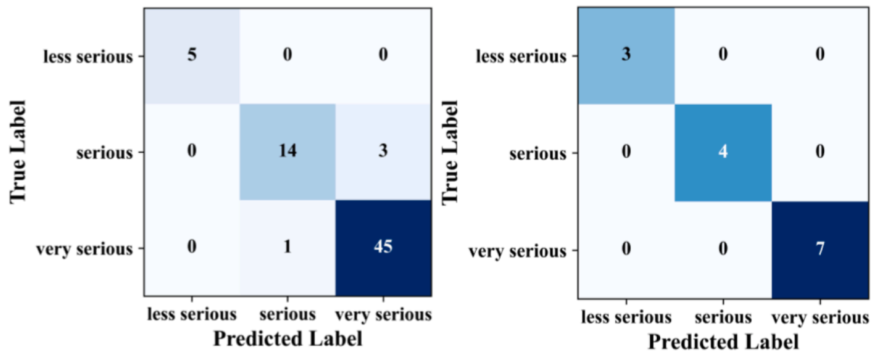

Fig. 7. Confusion matrix. (a) Confusion matrix of BN prediction results pre-COVID-19. (b) Confusion matrix of BN prediction results post-COVID-19.

Table 8
Risk level prediction results of BN model.

	less serious		serious		very serious	
	2017–2019	2020–2021	2017–2019	2020–2021	2017–2019	2020–2021
Accuracy	1	1	0.8235	1	0.9783	1
Precision	1	1	0.9333	1	0.9375	1
Recall	1	1	0.8235	1	0.9783	1
F-measure	1	1	0.8784	1	0.9579	1
Specificity	1	1	0.9804	1	0.8636	1
FPR	0	0	0.0196	0	0.1364	0
AUC	1	1	0.9787	1	0.9743	1

inferred that the model's prediction accuracy for maritime accident casualties is basically the same. According to Eq. (2) and the confusion matrix, the kappa coefficients of the two BN models are calculated to be 0.87 (2017–2019) and 1.0 (2020–2021), respectively. It is proven that the model in this paper can adapt to the problem of data and distribution imbalance.

5. Discussion and implications

5.1. Comparison of the number of accidents

The temporal evolution of maritime accidents is meticulously documented in Table 9. The data underscores a substantial decrease in maritime accidents following the advent of the COVID-19 pandemic. This trend invites a comprehensive examination of the contributing factors and their implications for the maritime industry, which facilitates the derivation of several pertinent conclusions regarding the pandemic's influence on maritime safety:

(1) Traffic flow variations: The pandemic's ripple effects on the global economy and trade have precipitated the closure or downsising of numerous ports. This has resulted in a significant alteration in ship traffic and volume, potentially leading to a shift in the frequency of maritime accidents.
(2) Personnel and equipment reductions: The exigencies of the pandemic have compelled some shipping entities and port authorities to curtail their workforce and operational equipment. Such adjustments may have inadvertently impacted the likelihood of maritime accidents occurring.
(3) Ship maintenance and inspection constraints: The imposition of pandemic-related restrictions has led to the cessation or reduction of essential ship maintenance and inspection services in some ports. This could have resulted in an increase in technical malfunctions aboard vessels, consequently heightening the risk of maritime accidents.
(4) Crew health concerns: The health and well-being of crew members are paramount to the safe operation of maritime vessels. The pandemic's impact on crew health, including the potential for illness-induced fatigue and errors, poses a significant risk factor for the escalation of maritime accidents.

Table 9
The number of maritime accidents over the pre- and post-COVID-19.

Year	This study	IMO GISIS
2017	144	451
2018	118	299
2019	75	304
2020	54	216
2021	11	163

5.2. A comparative analysis from the perspective of important RIFs

The analysis conducted in Section 4.1.1 reveals noteworthy shifts in the influential factors affecting maritime accidents between the periods of 2017–2019 and 2020–2021. During 2017–2019, the pivotal RIFs were determined as 'Type of accident', 'Ship operation', 'Ship type', 'Voyage segment', and 'Hull type', while for 2020–2021, they were identified as 'Type of accident', 'Ship type', 'Ship operation', 'Voyage segment', 'Ship age', 'Breadth' and 'Deadweight'. These findings underscore a dynamic evolution in the critical factors contributing to accident severity over time.

The emergence of new factors in the latter period, such as 'Ship age', 'Breadth' and 'Deadweight', could be indicative of the broader repercussions of the COVID-19 pandemic on the maritime industry. The inclusion of 'Ship age' can indicate potential delays in ship maintenance and renewal initiatives amidst heightened operational costs during the epidemic. Similarly, the introduction of 'Breadth' and 'Deadweight' may signify strategic adjustments by shipowners to address market uncertainties and dwindling demand, potentially resulting in alterations to cargo loads and vessel size.

Furthermore, these changes may also be intertwined with the deceleration of global economic activities during the pandemic. Reduced international trade could have prompted shipowners to prolong the service life of existing vessels due to diminished investment in new ships. Concurrently, in response to cost constraints and market challenges, ship operators might have opted for larger, wider, and heavier vessels to enhance operational efficiency, albeit at the expense of heightened operational complexities and risks.

Thus, it becomes evident that the impact of the COVID-19 pandemic on maritime accidents is multifaceted, encompassing shifts in operational strategies and broader economic dynamics. A nuanced comprehension of these transformations is imperative for devising effective maritime safety protocols and interventions aimed at mitigating accident risks during the pandemic. Scenario analysis within the context of specific settings will be necessary to reveal the multifaceted impact in detail.

5.3. Scenario analysis

5.3.1. Scenario 1: harsh environmental conditions

In the realm of marine accident risk assessment, scenario 1 delves into the intricate interplay among various parameters, including 'Time of day', 'sea condition', 'Visibility', 'Weather condition', 'Wind', 'Voyage segment', and 'Ship operation', particularly emphasising the influence of environmental factors on accident severity. Fig. 8 and Fig. 9 present simulations illustrating the probability distributions of diverse accidents across different environmental contexts. After rigorous iteration, it was ascertained that when the aforementioned factors align at 'night', 'bad', 'low', 'bad', 'high', 'river', and 'on passage', respectively, the vessel is highly susceptible to grave accidents, exhibiting the highest likelihood. This underscores that during practical maritime navigation, circumstances such as nighttime operations, harsh sea conditions, diminished visibility, inclement weather, elevated wind speeds, and navigation through riverine stretches may significantly heighten the risk of maritime mishaps.

Nighttime navigation often entails poor illumination, potentially impeding the vessel's ability to detect obstacles or other craft in a timely manner, thus elevating collision risks. Harsh sea and weather conditions, typified by towering waves, torrential rainfall, or thunderstorms, not only imperil the ship's stability and manoeuvrability but also pose threats of structural damage or capsizing. Reduced visibility, commonly associated with meteorological phenomena such as fog or precipitation, constrains the crew's situational awareness, augmenting the likelihood of collisions or groundings. High wind velocities can compromise the vessel's manoeuvring capabilities, precipitating deviations from the intended course, which can be particularly perilous in confined waterways or intricate channels. Furthermore, navigating through riverine expanses presents its own set of challenges, including tumultuous currents and variable water depths, thereby amplifying the risk of maritime incidents in such locales.

In light of these exigencies, it is imperative for both crew members and management personnel to maintain a state of heightened vigilance and possess adept emergency response capabilities to effectively mitigate potential hazards in real-time. Consequently, prudent navigation mandates a comprehensive assessment and adept management of these factors, coupled with the implementation of robust preventive and contingency measures, to safeguard the integrity and reliability of

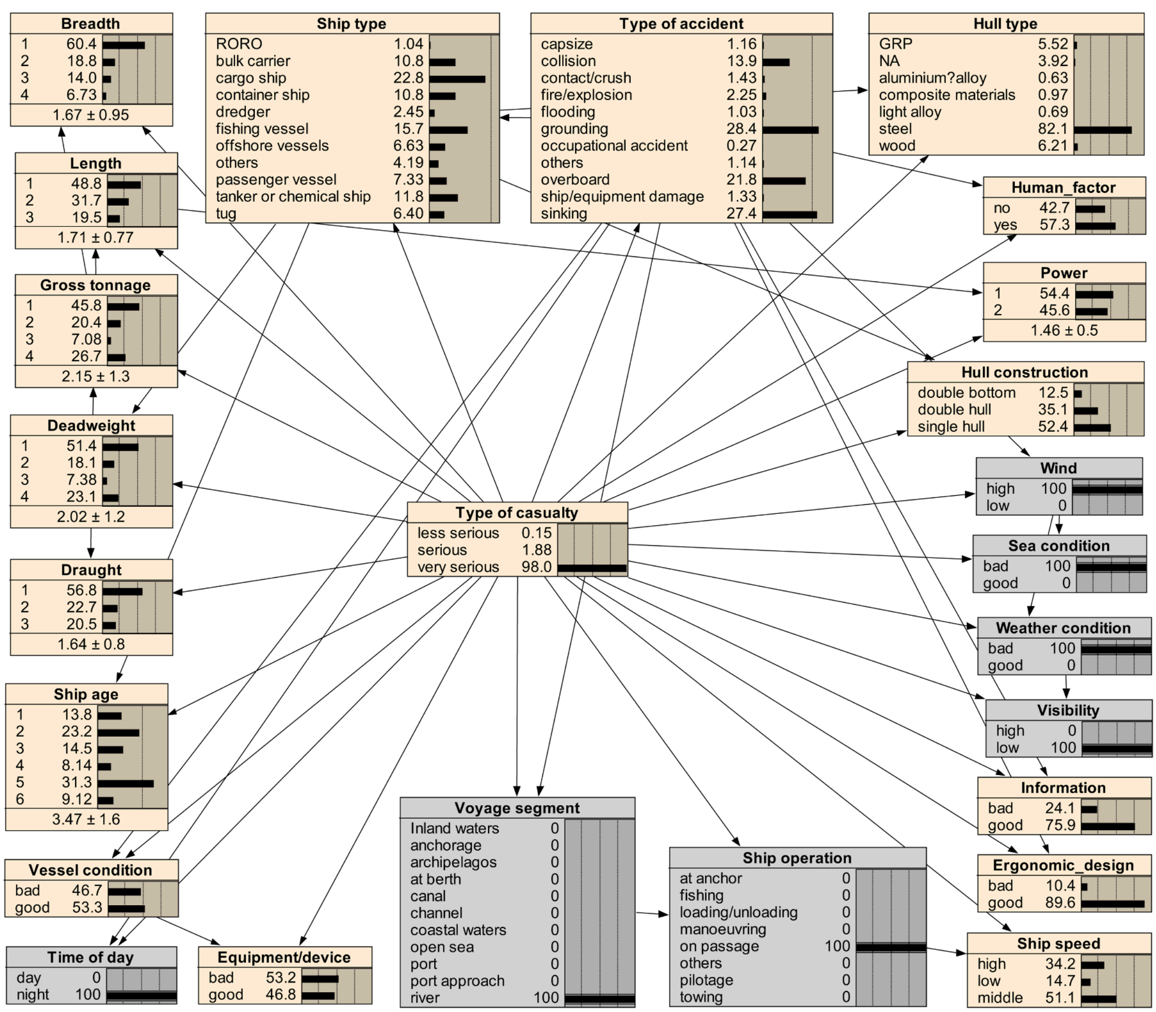

Fig. 8. The combined impact of environmentally-related RIFs on 'very serious' casualties before the COVID-19 outbreak.

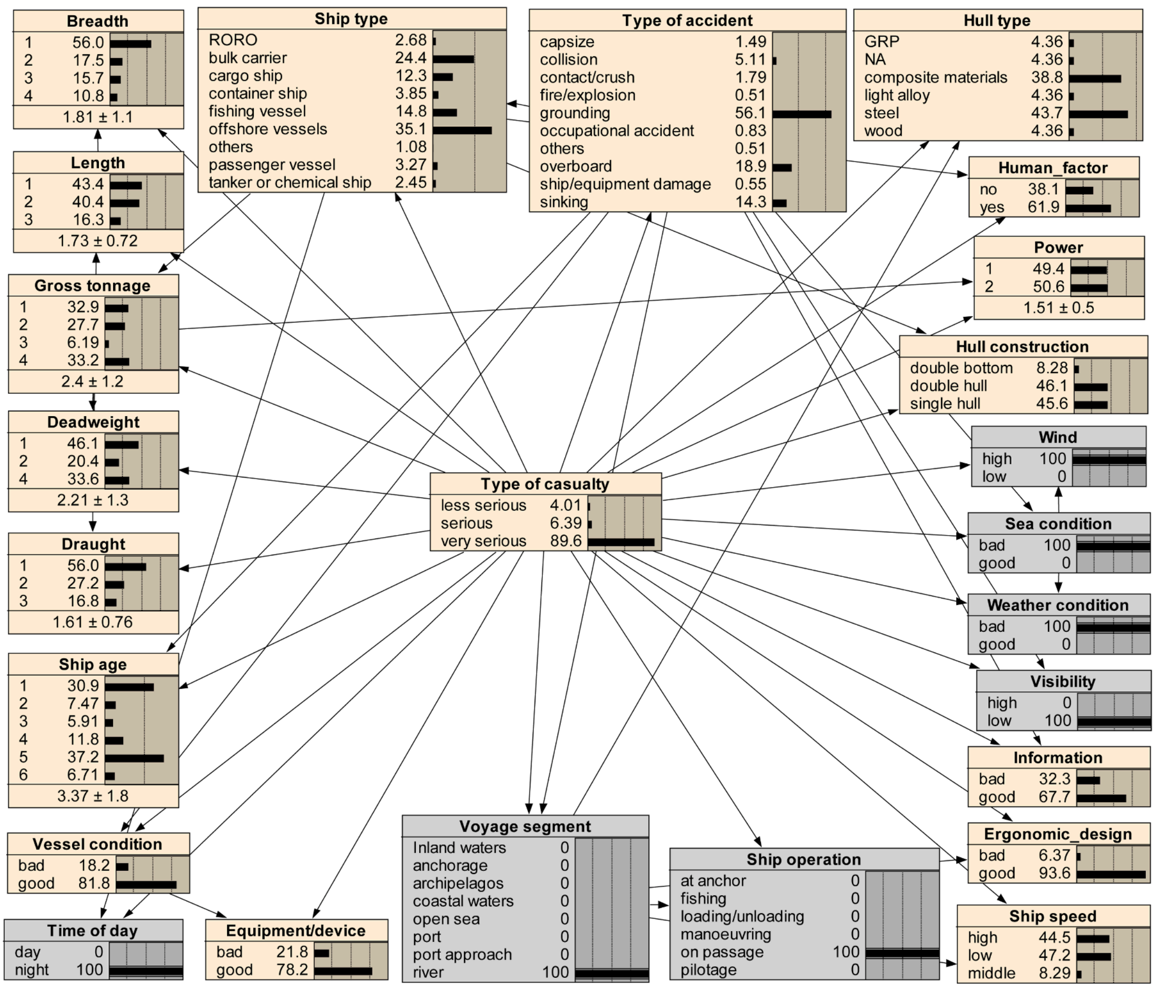

Fig. 9. The combined impact of environmentally-related RIFs on 'very serious' casualties after the COVID-19 outbreak.

maritime operations.

Analysis of simulation results shown in Table 10 reveals notable shifts in the characteristics of maritime accidents pre- and post-outbreak. Amidst the epidemic, a discernible downward trajectory in the incidence rate of severe accidents, plummeting from 98.0 % to 89.6 %, juxtaposes with a corresponding surge in the likelihood of grave accidents, emblematic of the multifaceted repercussions of the pandemic on accident severity. Notably, the prevalence of ground-contact incidents surged to 56.1 %, while occurrences of collision and sinking events dwindled. Such dynamics may be attributable to alterations in the maritime landscape during the epidemic period. For instance, there was a marked uptick in the proportion of offshore vessels and bulk carriers, concomitant with a decline in container ships and cargo vessels, mirroring the pandemic's sway over shipping demand and vessel selection.

Insights from maritime transportation expertise underscore the impact of the epidemic-induced supply chain disruptions and route re-alignments on shipping operations, thereby engendering a metamorphosis in accident typologies and severity levels. Consequently, stakeholders within the maritime domain, including shipping entities and regulatory bodies, are urged to remain vigilant vis-à-vis these evolving trends and institute efficacious safety management protocols to curtail both the frequency and magnitude of maritime mishaps, thereby safeguarding navigational integrity amidst turbulent times.

Table 10
Under the influence of environmental factors, the probability changes of different influencing factors pre- and post-COVID-19.

		2017–2019	2020–2021	Tendency
Type of casualty	less serious	0.15 %	4.01 %	↑
	serious	1.88 %	6.39 %	↑
	very serious	98.00 %	89.60 %	↓
Type of accident	grounding	28.40 %	56.10 %	↑
	collision	13.90 %	5.11 %	↓
	sinking	27.40 %	14.30 %	↓
	overboard	21.80 %	18.90 %	↓
Ship type	offshore vessels	6.63 %	35.10 %	↑
	bulk carrier	10.80 %	24.40 %	↑
	cargo ship	22.80 %	12.30 %	↓
	container ship	10.80 %	3.85 %	↓

5.3.2. *Scenario 2: impact of ship characteristics*

Scenario 2 examines how vessel-related RIFs influence accident severity, illustrated in Fig. 10 and Fig. 11. The results show that fishing vessels with wooden hulls, of unknown age, and in poor condition face the highest risks. High-risk characteristics also include a deadweight of 0–5000 tons, gross tonnage of 0–3000 GT, length of 0–100 m, breadth of 0–20 m, power of 0–3000 kW, draught of 0–6 m, and single-hull construction. Vessels with this combination of features are most likely to experience very severe accidents. These findings underline that vessel type, hull material, and operational condition are critical factors shaping maritime risk.

For instance, vessels outfitted with wooden hulls may exhibit heightened vulnerability to damage or accidents under certain circumstances, while idiosyncratic design flaws or equipment malfunctions could exacerbate accident probabilities. Consequently, stakeholders

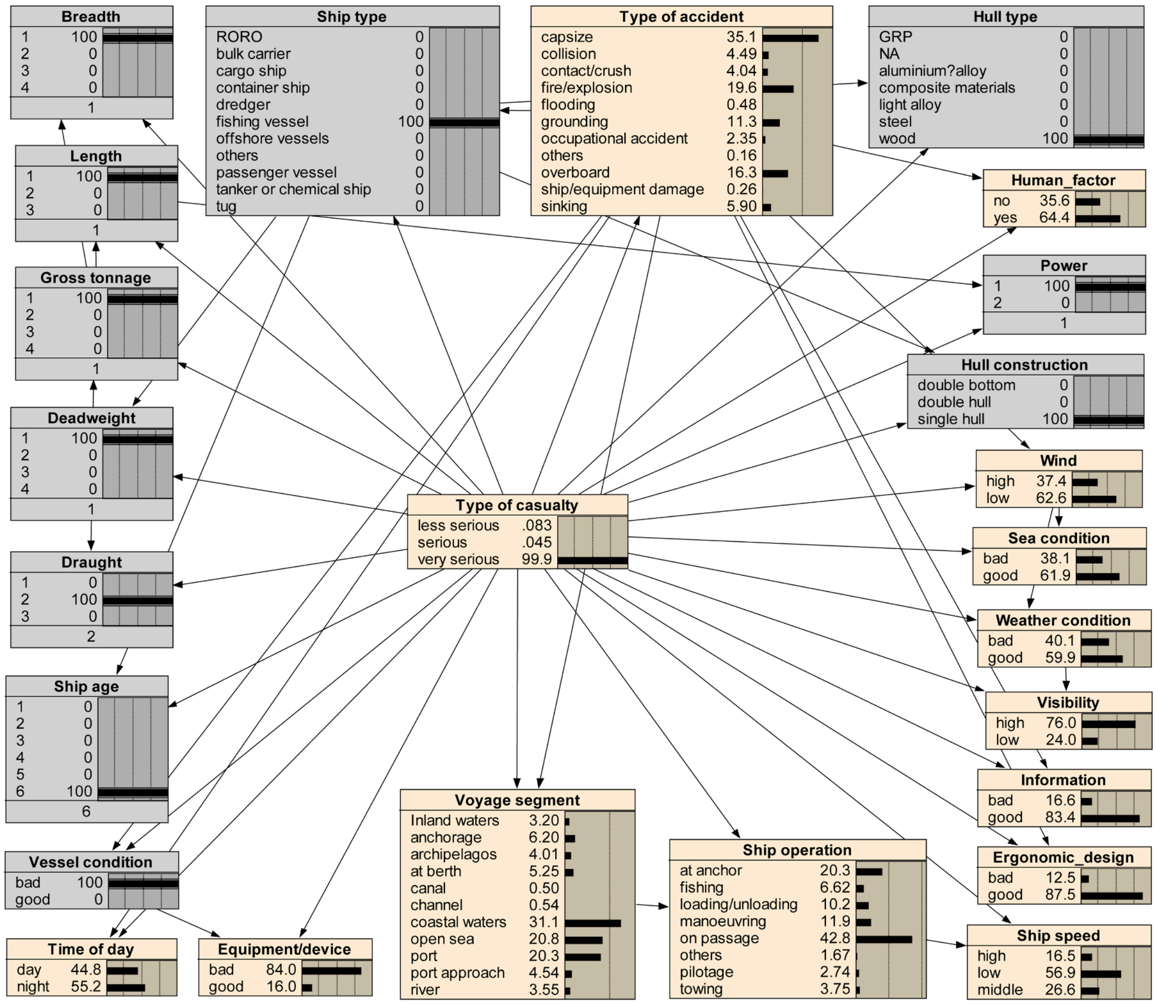

Fig. 10. Posterior probability analysis in 'very serious' type from ship-related factors pre-COVID-19.

encompassing shipowners, crew members, and regulatory bodies are enjoined to exercise heightened vigilance in the safe management and operation of such vessels, proactively instituting requisite precautions to mitigate accident risks, thereby fortifying both vessel integrity and crew safety.

Simulation findings elucidate the differential impact of ship characteristics on maritime accident dynamics pre and post the epidemic. As delineated in Table 11, the prevalence of capsizing incidents surged markedly to 83.1 % subsequent to the outbreak, indicative of a recalibration in ship transportation exigencies and operational modalities, or heightened susceptibility to capsizing owing to intensified vessel activities in coastal environs. Conversely, fire and explosion accidents decreased in the post-pandemic period, reflecting stricter safety protocols, targeted interventions, and improvements in maritime operational practices.

Moreover, there was a pronounced escalation in accident rates within coastal waters, soaring to 77.9 %, while incident frequencies in open seas and port locales registered a concomitant decline, suggestive of the realignment of maritime activities or the heightened prevalence of coastal conveyance operations. The increased frequency of accidents in fishing operations reflects the intensified activity within the fishing sector during the pandemic period.

These findings underscore the nuanced interplay between ship characteristics, operational dynamics, and environmental exigencies in shaping maritime accident trends amidst evolving socio-economic landscapes. Consequently, proactive measures encompassing robust safety frameworks, adherence to stringent standards, and the implementation of targeted interventions are imperative to mitigate accident risks, bolster navigational safety, and fortify resilience within the maritime domain in the wake of disruptive events such as global pandemics.

5.3.3. Scenario 3: reverse analysis from consequences to causes

Both scenarios outlined above have been subjected to prospective analysis utilising the BN model. Moreover, the versatility of the BN model extends to facilitating reverse analysis by examining the impact on variable nodes through adjustments in the target node status. In scenario 3, a deliberate inquiry into the most plausible circumstances surrounding incidents categorised as 'very serious' pre and post the COVID-19 outbreak is pursued. Herein, the probability value of the target node status is fixed at 100 % 'very serious', thereby elucidating alterations in the variable node 'Condition.' Fig. 12 and Fig. 13 elucidate the contextual particulars corresponding to 'very serious' accidents pre and post the COVID-19 pandemic, with the 'Type of Casualty' status of the target node held at 100 %.

Table 12 furnishes insights into shifts in influential factors following the COVID-19 outbreak, predicated on a 100 % probability of severe marine accidents. Notably, 'occupational accidents' and 'overboard incidents' have surfaced as predominant accident types post-pandemic, indicative of an uptick in crew members falling overboard. This underscores the imperative for ship managers to institute more stringent safety training regimens and deploy enhanced safety measures to safeguard the well-being of crew members against such perilous occurrences.

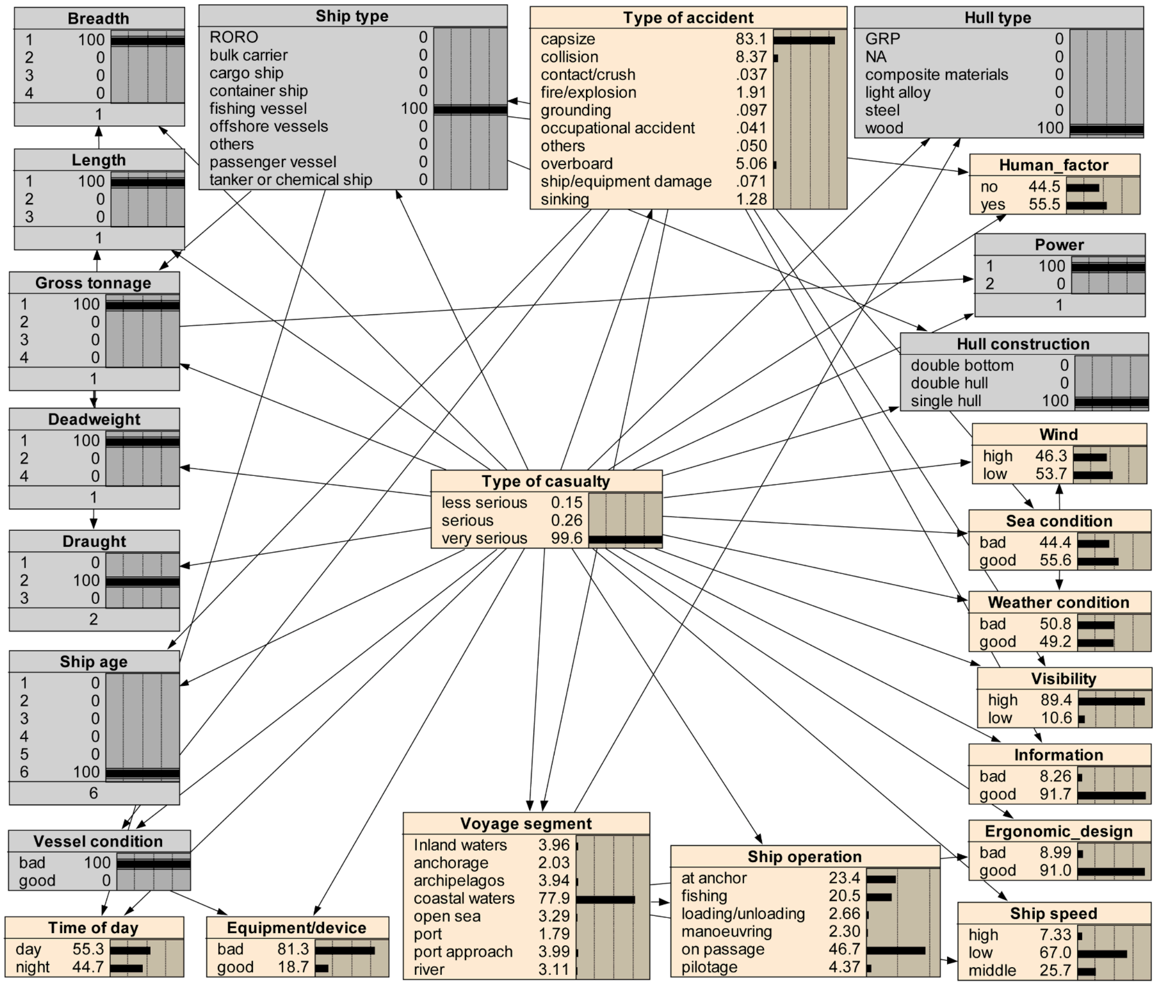

Fig. 11. Posterior probability analysis in 'very serious' type from ship-related factors post-COVID-19.

Table 11
Under the influence of the ship characteristics factors, the probability changes of different influencing factors pre- and post-COVID-19.

		2017–2019	2020–2021	Tendency
Type of accident	capsize	35.10 %	83.10 %	↑
	fire/explosion	19.60 %	1.91 %	↓
	overboard	16.30 %	5.06 %	↓
Voyage segment	coastal waters	31.10 %	77.90 %	↑
	open sea	20.80 %	3.29 %	↓
	port	20.30 %	1.79 %	↓
Ship operation	Fishing	6.62 %	20.50 %	↑
	Loading/ unloading	10.20 %	2.66 %	↓
	Manoeuvring	11.90 %	2.30 %	↓

Furthermore, a noteworthy transition is observed in ship typologies, with 'bulk carriers' supplanting the erstwhile prevalent 'cargo ships,' suggesting a surge in the deployment of large-scale bulk carriers within maritime transportation networks. Such vessels warrant heightened scrutiny and vigilant oversight during operational phases to uphold the integrity and safety of maritime endeavours. Concurrently, a discernible escalation in the probability of accidents transpiring in open seas is discerned, plausibly attributable to protracted long-distance voyages spanning global maritime routes. This necessitates the implementation of more rigorous safety protocols to ensure the secure navigation of vessels across expansive oceanic expanses.

Moreover, the heightened probability of 'on passage' operations post-pandemic signifies the proliferation of vessels embarking on extensive transcontinental journeys. This underscores the imperative for crews and ship managers to exercise heightened vigilance and prudence in navigating vessels, particularly during protracted long-haul voyages. Thus, it is incumbent upon ship managers and regulatory bodies to accord heightened attention to and adeptly manage scenarios encompassing crew-related accidents, the operation of large bulk carriers, transoceanic voyages, and extensive maritime traverses, thereby underpinning the safety and dependability of maritime traffic networks.

5.4. Implications

The findings of this study reveal a complex relationship between the COVID-19 pandemic, implemented safety measures, and maritime safety outcomes. By highlighting significant shifts in accident patterns, risk factors, and operational dynamics, this study provides valuable insights into the effectiveness of safety interventions and their broader implications for maritime stakeholders. To reflect these, the implications are structured into five key points.

(1) Effectiveness of pandemic safety measures.

This study assessed the effectiveness of key safety measures, including stricter port health inspections, reduced crew changes, mandatory quarantine, and enhanced digital reporting, by comparing accident patterns before and after the pandemic.

The effectiveness of these measures is evaluated through observed accident pattern changes. For example, reductions in collisions and fire/explosion incidents in Tables 9 and 10 suggest that stricter regulatory

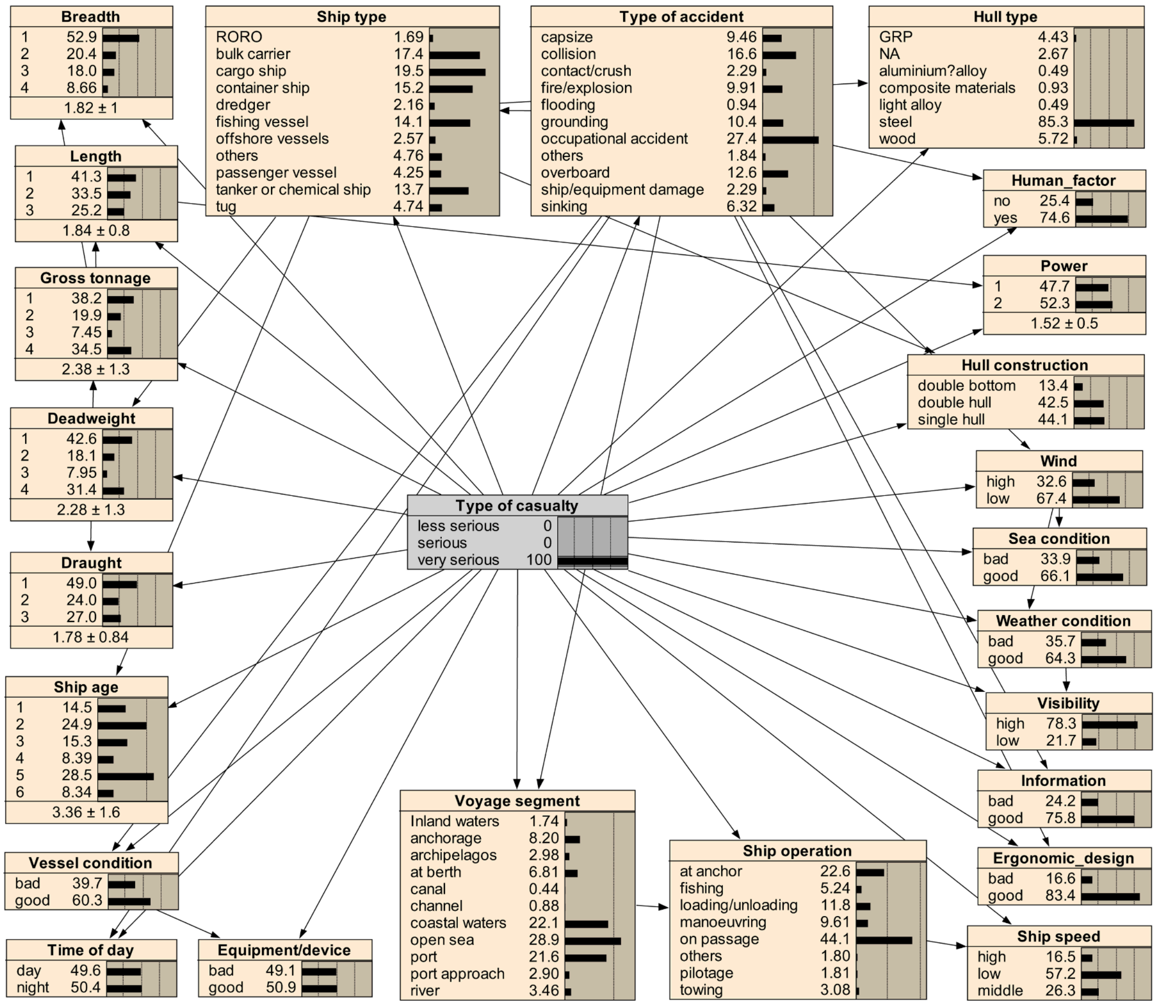

Fig. 12. Prior probability analysis in 'very serious' casualty type pre-COVID-19.

compliance, reduced port congestion, and remote oversight contributed positively to safety outcomes. Conversely, the increase in overboard incidents (from 12.6 % to 20.3 % in Table 12) indicates that some measures, particularly those limiting crew mobility and rotations, had unintended adverse effects on crew welfare. This dual impact underscores the need for balanced approaches that improve safety without overburdening seafarers.

(2) Pandemic impacts on maritime accident dynamics.

The overall decline in reported accidents (Table 9) occurred during the pandemic, partly due to global economic slowdowns and restricted shipping activity. However, accident typologies shifted. Bulk carriers were disproportionately involved in severe post-pandemic accidents, and overboard incidents rose (Table 10). These patterns reveal that while safety measures reduced some traditional risks, they also created new vulnerabilities linked to workforce stress, operational adjustments, and concentrated vessel activity.

(3) Structural shifts in vessel attributes and accident risk.

The analysis shows that 'breadth' and 'deadweight' became more influential RIFs after the onset of COVID-19. This aligns with external evidence indicating that containerships grew larger during this period (15–20 % increase according to Clarkson), while dry bulk carriers remained stable and oil tankers saw few new deliveries, with large vessels continuing to dominate but without a notable size change. Hence, the increased influence of breadth and deadweight in our model is likely driven by the size growth of containerships rather than uniform trends across all ship types. Larger breadth and higher deadweight are directly associated with reduced manoeuvrability, stability constraints, and grounding risks, particularly in confined waterways and congested port approaches. Their heightened influence therefore reflects genuine changes in fleet composition and operational exposure, rather than a statistical artifact.

(4) Strategic adjustments for stakeholders.

The BN model outputs and TRI-based scenario analysis point to actionable strategies. For ship operators, the rise in capsizing and overboard risks (Tables 11–12) highlights the need for reinforced stability checks, stricter maintenance adherence, and enhanced fall protection systems. For regulators, declining collision rates but rising ground-contact incidents suggest a need for digitalised COLREGs oversight and improved remote inspection tools (Table 10). For port authorities, the higher probability of severe accidents in poor visibility and high-wind scenarios (Figs. 8–9) demonstrates the importance of enhanced meteorological monitoring, dredging, and night navigation support. For supply chain managers, the shift from container ships (10.8 % to 3.85 %) to bulk carriers (10.8 % to 24.4 %) (Fig. 7) underscores the importance of adaptive routing strategies and predictive analytics. From a broader regulatory perspective, these results also indicate the need to adjust inspection priorities to focus on vessel categories most exposed to post-pandemic risks, such as bulk carriers and fishing vessels.

By directly linking simulation results to stakeholder actions, the findings provide a structured roadmap for evidence-based policy and operational reform.

(4) Crew welfare and long-term safety considerations.

The BN analysis of occupational safety scenarios (Figs. 12–13) shows rising probabilities of overboard and open-sea incidents (28.9 % to 42.6

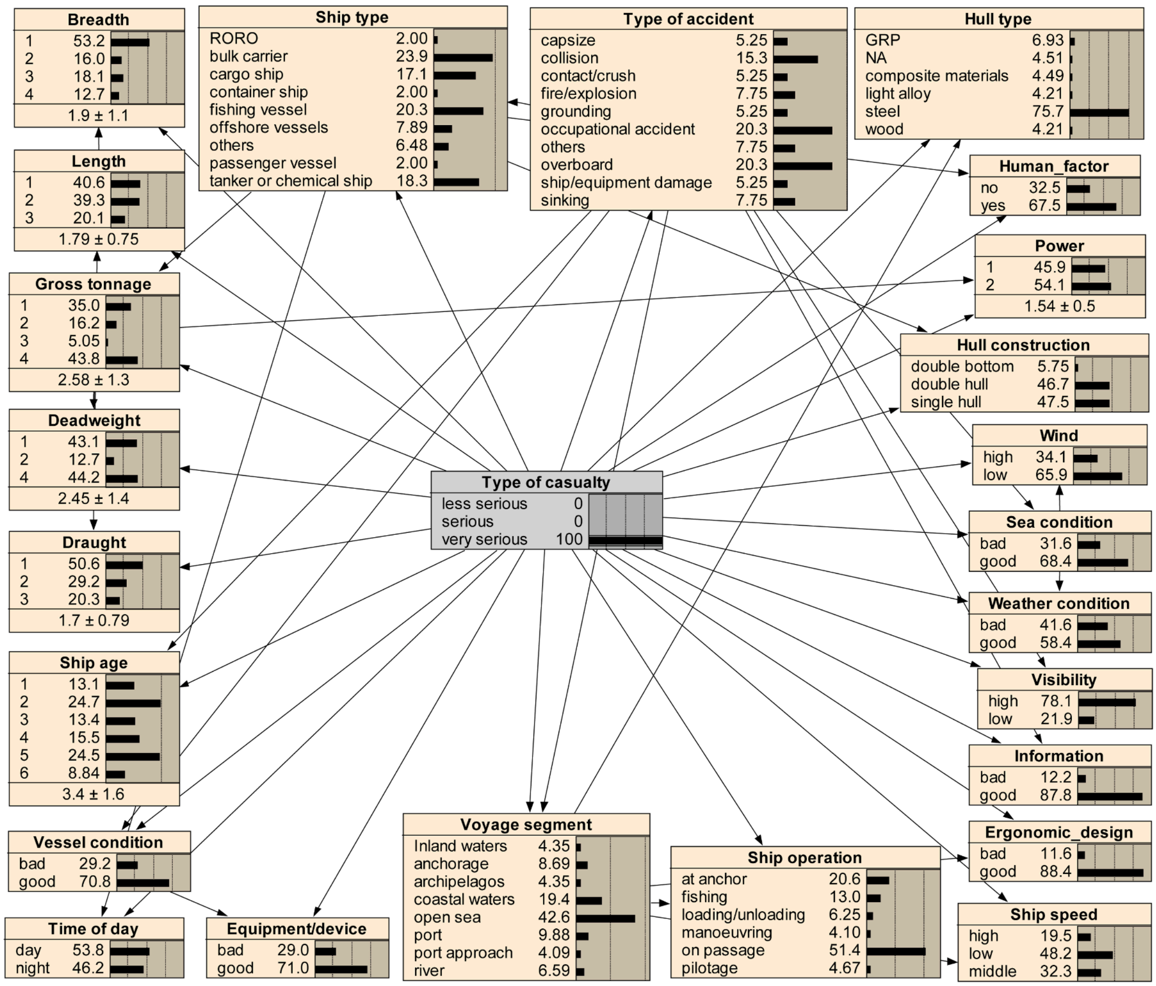

Fig. 13. Prior probability analysis in ‘very serious’ casualty type post-COVID-19.

Table 12
When the probability of a maritime accident being ‘very serious’ is 100 %, the probability changes of related influencing factors pre- and post-COVID-19.

		2017–2019	2020–2021	Tendency
Type of accident	occupational accident	27.40 %	20.30 %	↓
	overboard	12.60 %	20.30 %	↑
Voyage segment	open sea	28.90 %	42.60 %	↑
	port	21.60 %	9.88 %	↓
Ship type	cargo ship	19.50 %	17.10 %	↓
	bulk carrier	17.40 %	23.90 %	↑
Ship operation	on passage	44.10 %	51.40 %	↑
	loading/unloading	11.80 %	6.25 %	↓
	manoeuvring	9.61 %	4.10 %	↓

%), reflecting increased long-haul voyages and reduced crew changes. These trends align with the qualitative interpretation of fatigue and isolation risks in Section 4.2. Thus, implications extend beyond technical fixes: mental health monitoring, regulated crew rotation, and onboard psychological support systems should be prioritised alongside training and safety culture initiatives.

By systematically learning from the COVID-19 experience, the maritime industry can design resilient frameworks to manage not only pandemics but also other large-scale disruptions such as geopolitical conflicts or canal blockages.

5.5. Extension to other crisis scenarios and future directions

Although this study focuses specifically on the COVID-19 pandemic, the proposed BN–based framework is not limited to pandemic-related disruptions. The methodological foundation, linking RIFs with accident outcomes through probabilistic reasoning, is sufficiently flexible to accommodate a wide range of large-scale crisis scenarios, provided that relevant datasets are available.

For example, crises such as the Suez Canal blockage (2021), the Red Sea geopolitical disruptions, or future large-scale port closures could be analysed using the same framework. By adjusting the input dataset to reflect accident reports, vessel traffic records, or operational disruptions specific to these crises, the model could capture how risk factors and accident probabilities shift under different external pressures.

In practical terms, the framework could be extended in two directions:

Crisis-specific RIFs: Introducing additional risk factors unique to non-pandemic crises (e.g., navigational constraints in canal blockages, security threats in conflict zones).

Comparative scenario analysis: Applying the model to multiple crises to identify common vulnerabilities versus crisis-specific risk patterns, thereby supporting proactive preparedness strategies.

This study demonstrates that pandemic-induced changes have lasting effects on accident causation patterns. Building on this, future research should focus on: Integrating AIS, port congestion, and real-time monitoring data with BN models, assessing the long-term impacts of reduced workforce availability and delayed maintenance, developing

AI-driven predictive risk models for evolving operational patterns, and evaluating the effectiveness of crisis-response mechanisms across different regulatory regimes.

These directions will advance the applicability of the framework and enhance its value as a decision-support tool for managing diverse maritime crises.

6. Conclusions

This research analyses the profound effects of the COVID-19 pandemic on maritime safety, meticulously examining the evolution of maritime accident trends before and after the pandemic's onset. By meticulously analysing extensive datasets from the GISIS and the IHS-LRF database, this study has pinpointed pivotal factors that shape maritime accident trends and appraised the effectiveness of prevailing safety protocols. Our analysis, grounded in a data-driven BN framework, has unveiled the pandemic's profound imprint on maritime safety dynamics, highlighting shifts in safety paradigms and the advent of unprecedented risk factors. The altered shipping patterns and the challenges posed by regulatory compliance in the wake of the pandemic have emerged as specific risks, which our study has objectively quantified. The implications of these findings are far-reaching for policymakers, industry stakeholders, and maritime professionals. They underscore the necessity for a nuanced understanding of the post-COVID-19 maritime safety landscape to inform strategic decisions aimed at bolstering safety measures and mitigating the risks of maritime accidents.

From a practical perspective, the findings can support the IMO and flag states in updating risk management guidelines, particularly by prioritising vessel categories and operational phases that showed heightened accident involvement during the pandemic. The demonstrated robustness of the TAN framework also highlights its readiness for integration into digital decision-support systems, enabling probabilistic risk assessment to be embedded within operational monitoring platforms. Specific use cases include: guiding port state control in tailoring inspection priorities toward higher-risk vessel types (e.g., bulk carriers and fishing vessels); assisting shipowners in adopting targeted stability and occupational safety measures; and enabling classification societies to refine rules relating to vessel breadth, deadweight, and stability under crisis conditions.

The restricted post-crisis period (2020–2021) constrains the ability to capture long-term or delayed impacts of the pandemic, such as those arising from prolonged crew fatigue, deferred maintenance, or evolving trade patterns. As more accident data and records become available from 2022 onwards, future research will expand the dataset to enable a more robust comparative analysis and better distinguish between short-term disruptions and long-term structural changes in maritime safety. Another limitation concerns class imbalance: 64.9 % of cases are classified as 'very serious,' which may bias the model toward the majority class. While the real-world distribution was preserved here, future work will explore rebalancing strategies to improve minority class detection.

Looking forward, there remains an imperative need for further research to uncover additional determinants of maritime accidents and to refine predictive models that can better anticipate and mitigate these risks. For instance, the data could be reclassified based on the different stages of COVID-19 response across countries (e.g. national quarantine periods) to enable a more in-depth analysis of the impact. While acknowledging the limitations inherent in our study, it nonetheless enriches the maritime safety discourse, offering a robust foundation for future research endeavours and policy formulation within the maritime sector.

CRediT authorship contribution statement

Huanhuan Li: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Hang Jiao:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Zhong Shuo Chen:** Writing – review & editing, Visualization, Validation, Investigation, Formal analysis. **Jasmine Siu Lee Lam:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Zaili Yang:** Writing – review & editing, Visualization, Validation, 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.

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Data availability

Data will be made available on request.

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