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An integrated multidimensional model for heterogeneity analysis of maritime accidents during different watchkeeping periods

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ABSTRACT

The navigational safety of ships can be impacted by factors such as varying weather conditions, sea states, circadian rhythms and crew physical conditions at different times of the day. Despite numerous studies in the maritime accident field, systematic investigations on the heterogeneous characteristics of accident Risk Influential Factors (RIFs) across different watchkeeping periods remain limited. To address this gap, this study pioneers a multidimensional analysis framework which integrates an Enhanced Multilevel Association Rule Mining (EMARM) algorithm, the Weighted Influence Non-linear Gauge System (WINGS), the Total Adversarial Hasse Diagram Technology (TAHDT), and the Matrices Impacts Croises-Multiplication Appliance Classement (MICMAC). Firstly, the innovative EMARM algorithm is proposed to identify frequent itemsets and enhanced multilevel association rules between RIFs, i.e., at the state level and factor level. Secondly, the WINGS is established in a data-driven manner and employed to elucidate the causality among these RIFs, providing insight into their interactions. Thirdly, the improved TAHDT, a game theory-based method is utilized to establish hierarchical relationships between RIFs, revealing critical interdependencies and causal pathways. Finally, based on the driving forces and dependencies of RIFs, the MICMAC is applied to classify the RIFs and dig their roles within the system. The results indicate a significant heterogeneity in the critical RIFs across different watchkeeping periods, such differences highlight the unique needs of safety management strategies in each period. By clarifying the challenges, the proposed framework offers a new perspective for improving bridge resource management onboard and further contributing to reducing accident occurrences.

1. Introduction

Maritime transport plays a crucial role in international trade and global supply chains, accounting for approximately 90% of all goods traded internationally (Aydin et al., 2024). Maritime accidents are one of the biggest obstacles to sustainable maritime trade. Between 2014 and 2020, the European Maritime Safety Agency reported 22,532 maritime accidents in Europe, involving 8015 ships and resulting in 6921 injuries (European Maritime Safety Agency, 2021). These serious consequences of maritime accidents are drawing attention in the shipping industry. Statistics indicate that 75%–96% of maritime accidents are actually attributed to human factors (Fan et al., 2020; Song et al., 2024; Yang et al., 2023). As a result, ensuring the correct operations of crew members and the effective bridge resource management plays a crucial role in navigational safety (Chen et al., 2024).

In practice, all operations onboard a ship largely depend on the professional expertise of the ship's crew (Jiang et al., 2025; Misas et al., 2024; Zhang et al., 2025). The performance of the ship crew at the operation site is one of the most critical factors in ensuring the work is carried out safely (Utne et al., 2019). Particularly, as key members of the bridge team, the ship master, the chief, second, and third officers are responsible for ensuring a vessel's safe navigation and responding to

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potential emergencies. The 24-h watchkeeping periods during a ship's voyage is a standard procedure, which is normally rotated among the chief, second, and third officers. These officers are responsible for navigational watch, GMDSS operations, and a range of critical tasks, including ensuring safe navigation, collision avoidance, weather monitoring, and responding promptly to emergencies. However, it is important to note that watchkeeping arrangements may vary across different companies or ships. In some cases, particularly where cargo operations are highly complex and the chief officer is solely in charge, the high workload may preclude the chief officer from serving as a watchkeeping officer. Instead, additional officers of other ranks might assume responsibility for specific watch periods, such as the 4–8 and 16–20 watchkeeping period. Nevertheless, this study focuses on the standard arrangement where the chief, second, and third officers all participate in the watchkeeping rotation. Although the daily navigational watch duration is the same for the chief, second, and third officers (i.e., 8 h per person), the navigational safety of ships can be impacted by varying weather conditions, sea conditions, circadian rhythms, and crew physical conditions at different times of day (Feng et al., 2025; Filtz et al., 2015). For example, navigation conditions may be relatively favourable during the day when the weather is clear and the sea is calm. In contrast, the night-time navigation can be more challenging due to the absence of natural light and the crew's physiological condition, requiring the duty officer to rely on navigational equipment. Therefore, different watchkeeping periods are showing heterogeneous characteristics. The investigation of such varying Risk Influential Factors (RIFs) contributes to understanding potential risks faced by different duty officers, which can further minimize the risk by tailoring targeted safety measures and training programs for the onboard crew at various times of the day. To our best knowledge, this topic still remains unexplored, and this study aims to fill in this gap by using an integrated multidimensional analysis framework, which integrates an Enhanced Multilevel Association Rule Mining (EMARM) algorithm, the Weighted Influence Non-linear Gauge System (WINGS), the Total Adversarial Hasse Diagram Technology (TAHDT), and the Matrices Impacts Croises-Multiplication Appliance Classement (MICMAC).

The subsequent parts of this paper are structured in the following manner: Section 2 provides a review of pertinent literature on the risk analysis of maritime accidents, including their methodological approaches. Section 3 outlines the data sources and methodologies employed. Section 4 discusses the findings from multiple perspectives and analyses them thoroughly. Section 5 assesses the importance of this research from both theoretical and practical standpoints and proposes recommendations. Lastly, Section 6 concludes the study and suggests directions for future research.

2. Literature review

2.1. Research on the heterogeneity of maritime accidents

In recent years, research on the heterogeneity of maritime accidents has expanded to explore various aspects, e.g., accident characteristics under different weather conditions, regions or waters, ship age or types, crew qualifications, and ship speed (Cao et al., 2024b, 2025, ; Feng et al., 2025). Brandt et al. (2024) examined the differential impact of various weather conditions on different types of maritime accidents. Huang et al. (2023) analysed the regional disparities in accident distribution, highlighting variations in the number of accidents across different sea areas. Zhang et al. (2022) compared two sea areas with high accident densities, identifying key RIFs influencing fatality and injury outcomes, and suggested that regional characteristics significantly affect these outcomes. Cao et al. (2024b) investigated maritime accidents across different ship types and found notable differences in critical RIFs between ship types. Eleftheria et al. (2016) statistically analysed the impact of ship age and types on accident frequency. Berg et al. (2013) identified crew experience, communication skills, and background knowledge as critical for safety in complex navigational environments. Chang and Park (2019) revealed that higher speeds typically increase the risk of collision, while lower speeds raise the risk of grounding.

During sea voyages, navigational officers work in 24-h watch to ensure continuous ship operations. The circadian rhythms have certain effects on crew physical conditions, and further on the operational risk of ships. Branch et al. (2004) observed that accident rates are higher under the 6-h work, 6-h rest (6-6) watch system, which is commonly used on smaller vessels or in specific operational contexts. The frequent watch in this system makes it difficult for crew members to obtain sufficient continuous sleep, increasing the likelihood of accidents. The frequent watch in this system makes it difficult for crew members to obtain sufficient continuous sleep, increasing the likelihood of accidents. In contrast, Størkersen et al. (2012) found that while different duty regimes influenced crew fatigue levels to some extent, they had minimal impact on navigational safety. van Leeuwen et al. (2021b) further explored the variability in how different watch systems affect the alertness of duty officers. Both Heikkila (2016) and Shi et al. (2021) noted that a well-designed watch system can improve duty alertness and reduce ship navigational risks. Devereux (2022) examined the relationship between seafarers' risk of injury and the total watchkeeping duration, finding that the risk was higher at the beginning and middle of the duration but declined toward the end. Ugurlu et al. (2018) noted that early morning watch lead to crew fatigue and poor psychological conditions, while improper crew operations are a common RIF during night watch. Vinagre-Ríos et al. (2021) further observed that accidents during the night watch tend to be more severe than those during the day.

2.2. Research on accident causality analysis methods

A substantial body of research has focused on analysis of maritime accidents. Currently, the primary research methods include, but are not limited to, the Analytic Hierarchy Process (AHP) (Xiao et al., 2024), Structural Equation Modelling (SEM) (Xu et al., 2021), and machine learning techniques such as regression analysis and Bayesian Networks (BN) (Aydin et al., 2024; Xing et al., 2023a).

In studies of accident causality, the Weighted Influence Non-linear Gauge System (WINGS) has proven to be an effective analytical method. Originating from Decision-making Trial and Evaluation Laboratory (DEMATEL), WINGS is designed to analyse intertwined factors and their causal relationships (Tavana et al., 2023). Wang and Zhang (2022) proposed an approach that combines grey theory with WINGS to identify critical factors and their corresponding causal relationships in agricultural green supply chain management. Cao et al. (2024a) applied the WINGS and association rule mining (ARM) technique to study the RIFs of maritime accidents, successfully identifying the key RIFs associated with different ship types. The experimental results indicated that the WINGS model combined with ARM outperformed the DEMATEL method.

The complexity, multidimensionality, and interconnectedness of RIFs in maritime accident analysis pose significant challenges for a single approach to comprehensively and effectively address the issues. For high-dimensional RIFs, an analytical method capable of classifying them into distinct levels and categories is essential. The Hasse Diagram Technique (HDT) serves as a graphical representation that can identify and illustrate the relationships and priorities among RIFs. In the field of food safety, Zhu and Liu (2020) employed the HDT method for hierarchical analysis of infant milk powder data in China, demonstrating its effectiveness in analysing the main factors influencing the safety of infant milk powder. Sun et al. (2024) proposed a comprehensive assessment framework integrating an improved version of DEMATEL and HDT to evaluate the low-carbon transition quality of energy-intensive industries in China. Their findings indicated that the combination of DEMATEL and HDT mitigated the information loss associated with multi-criteria decision-making approaches, which may map multiple indicators to a single outcome, and significantly enhanced the adaptability and applicability of the indicator system and assessment methodology.

Although WINGS and HDT can individually contribute to the analysis of RIFs in maritime accidents, they still exhibit deficiencies in aspects such as dynamics and complexity (Xing et al., 2023a, 2023b). A comparative analysis of results from multiple methods is anticipated to compensate for these shortcomings through the complementarity of each method's strengths. The Matrices Impacts Croises-Multiplication Appliance Classement (MICMAC) is a technique designed to analyse interactions among multiple factors in complex systems. It can be employed for classification and driver-dependency analysis, thereby complementing and validating results from other methodologies and providing a more comprehensive and in-depth analytical perspective (Xing et al., 2023a). For instance, Xing et al. (2023b) compared the results of the MICMAC method with those from other approaches, such as DEMATEL, successfully identifying key RIFs related to fire safety. Similarly, Janssen et al. (2019) utilized a combination of Interpretive Structural Modelling (ISM) and MICMAC to identify significant challenges related to the Internet of Things in smart cities. Their findings indicated that the integration of these two approaches yields better insights into challenges and potential solutions. Furthermore, Xing et al. (2023a) combined DEMATEL, ISM, and MICMAC approaches to explore factors influencing the lifting quality of large offshore structures. This combined methodology proved effective in revealing intrinsic links among RIFs and analysing their interactions.

2.3. State of the art and contributions of this study

This study offers four significant contributions to the field of maritime accident analysis, providing novel perspectives and insights into maritime safety. The state-of-the-art for these contributions (N1-N4) is summarized below.

N1. A new perspective on maritime accident analysis: Heterogeneous study of different watchkeeping periods.

State of the art: The current literatures primarily focus on the study of maritime accidents across various accident waters and ship types (Cao et al., 2024b; Zhang et al., 2022). However, analyses of relevant RIFs associated with maritime accidents during different watchkeeping periods (e.g., third, second, and chief officers) remain insufficient. This gap results in a lack of theoretical foundations and practical guidance for safety management measures that address the heterogeneity of different watchkeeping periods.

Our solution: This study clarifies the accident characteristics associated with different watchkeeping periods by refining the classification of maritime accident data. This approach not only addresses the existing literature gap concerning accident characteristics during different watchkeeping periods but also provides a crucial theoretical foundation and practical guidance for safety management measures tailored to the heterogeneity of various watchkeeping periods.

N2. An improved data mining approach: Enhanced multilevel association rule mining algorithm.

State of the art: Traditional ARM techniques can only reveal the associations between RIFs at the state level (Cao et al., 2024a), exhibit limitations in identifying complex associations and fail to adequately capture the effects of multiple factor levels. This inadequacy adversely impacts the accuracy and comprehensiveness of analysis results.

Our solution: This study proposes an improved data mining method, EMARM, which is capable of identifying multi-level coupling relationships inherent in maritime accident RIFs, i.e., at the state level and factor level. This method can extract hidden patterns and associations from large volumes of accident data by integrating coupled RIFs at various levels, thereby revealing the connections between RIFs more comprehensively and accurately.

N3. An improved hierarchical analytical approach: Game theory-based total adversarial Hasse diagram technology.

State of the art: While HDT is a valuable tool, it may struggle to effectively analyse the impacts of complex RIFs on systems characterized by significant uncertainty, potentially leading to the oversight of critical RIFs in practical applications (Ding et al., 2022).

Our solution: This study incorporates game theory into HDT, optimally combining subjective and objective allocation methods to yield the most reasonable weights. Consequently, the TAHDT addresses the limitations of traditional HDT when confronting dynamically changing and adversarial scenarios. This provides a more comprehensive, in-depth, and robust analysis, making it better suited to the uncertainty and adversarial contexts of maritime accidents.

N4. An integrated multidimensional analytical model: EMARM-WINGS-TAHDT-MICMAC (EWTM) model.

State of the art: Traditional accident analysis methods often rely on a single analytical tool, which limits their ability to fully integrate multiple analytical perspectives (Feng et al., 2024a). This limitation hampers the comprehensive identification of various factors affecting accidents, leading to one-sided analyses.

Our solution: This study pioneers the construction of an integrated multidimensional analytical model, EWTM, which combines a machine learning method, a causal analytical method, a structured hierarchical approach, and system analysis technique. The EWTM model provides a holistic view of key RIFs associated with maritime accidents across different watchkeeping periods, enhancing both the depth and breadth of accident analysis.

3. Materials and methodology

This study combines EMARM, WINGS, TAHDT, and MICMAC methods to propose an integrated multidimensional analytical model for maritime accident analysis. Firstly, the EMARM algorithm is developed to mine maritime accident data from different watchkeeping periods, revealing Enhanced Multilevel Association Rules (EMARs) among the RIFs. Secondly, the WINGS is established in a data-driven manner and utilized to determine the reason and centrality degrees, as well as the weight of the RIFs, enabling an in-depth analysis of their causal relationships. Following this, the improved TAHDT approach is utilized to uncover internal linkages among RIFs and delineate their logical hierarchical structures. Finally, the MICMAC method is used to calculate the driving force and dependency of each RIF, followed by a classification analysis. This study identifies the key RIFs affecting maritime accidents across different watchkeeping periods through multidimensional analyses, and provides tailored recommendations to enhance navigation safety specific to each watchkeeping period. The research flow of this study is illustrated in Fig. 1.

3.1. Research data

In this study, the marine accident investigation reports from 2000 to 2019 were collected from the databases of seven global maritime agencies: The China Maritime Safety Administration (China MSA), the Federal Bureau of Maritime Casualty Investigation (BSU), the National Transportation Safety Board (NTSB), the Japan Transportation Safety Board (JTSB), the Australian Transport Safety Board (ATSB), the Canadian Transportation Safety Board (TSB), and the Marine Accident Investigation Branch (MAIB). Fig. 2 illustrates the sources and distribution of these marine accident investigation reports.

The review of marine accident investigation reports from the specified database highlighted discrepancies in the detail level across different countries, with some entries showing inaccuracies or lacking completeness. To ensure data authenticity and completeness, reports with missing or incomplete data were excluded. For instance, reports lacking details about environmental factors contributing to the accident were removed following the implementation of this criterion. A detailed account of the screening process for these accident investigation reports is provided in prior studies (Cao et al., 2023; Feng et al., 2024a, 2024b; Wang et al., 2021). The data pre-processing was conducted in three

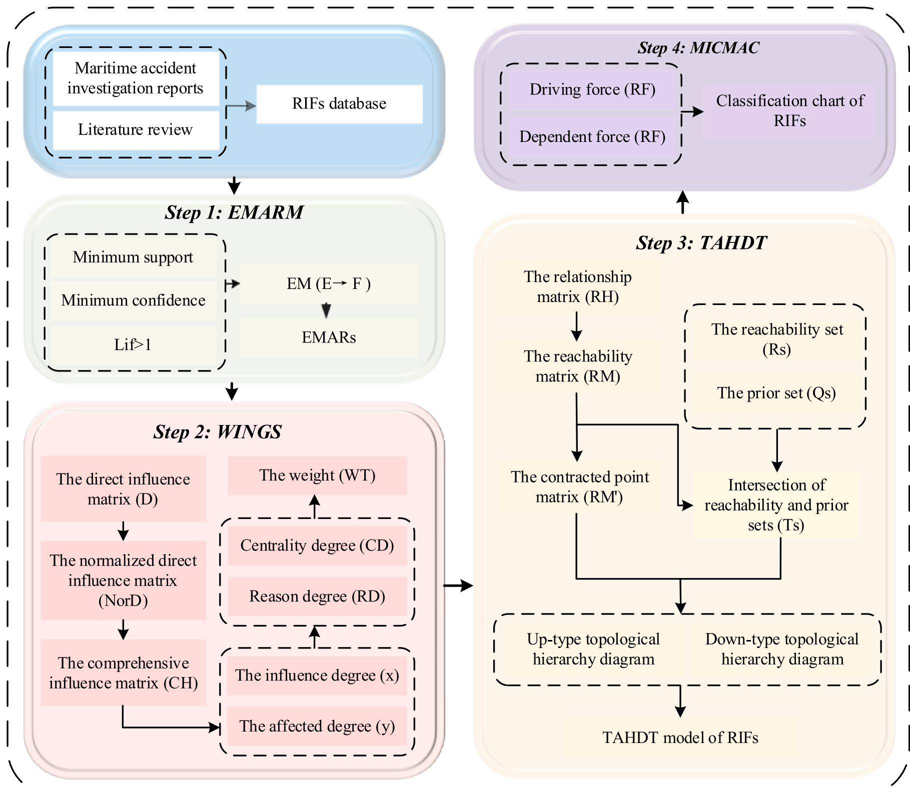

Fig. 1. Research flow chart of this study.

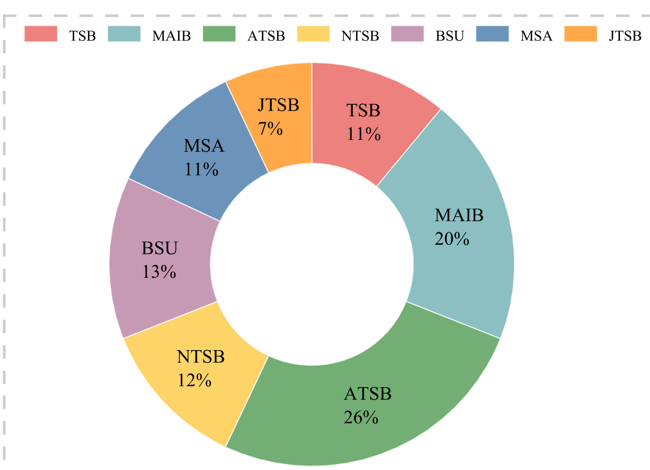

Fig. 2. The sources distribution of marine accident investigation reports.

stages. Firstly, duplicate accident reports were filtered out, resulting in a total of 1294 accident reports. Secondly, based on 1294 maritime accident investigation reports from 2000 to 2019, this study classifies the accidents into three categories according to watchkeeping periods, corresponding to the watch of the chief, second, and third officers. Fig. 3 shows that the number of accidents was similar during the watchkeeping periods of the chief, second, and third officers. Finally, a first-level RIFs indicator system was developed, including human factors, ship factors, environmental factors, and management factors, along with 34 second-level RIFs. This system was designed from system safety engineering viewpoint, drawing on relevant studies and expert opinions (Wang et al., 2023; Xiao et al., 2024). The categories of RIFs and their descriptions are specified in Table A of Appendix A. In the human factors category, the seafarer's physical and psychological state is classified as either "poor" or "good" based on explicit descriptions in the accident reports. Specifically, when the reports mention conditions such as fatigue, depression, or drowsiness, the seafarer's state is categorized as "poor," whereas a generally healthy or alert condition is categorized as "good." Similarly, the educational background of the seafarer is evaluated based on the reports, where indications of limited formal education or insufficient qualifications for the held position are categorized as "poor," while meeting or exceeding the required standards is categorized as "good." Fig. 4 illustrates the distribution of maritime accident types and the severity of accidents based on their occurrences in the accident dataset. It is intended primarily to provide a statistical overview of the distribution and frequency of various accident types across different watchkeeping periods. While this visualization serves as a foundational component for understanding the general trends in maritime accidents, but it is important to note that this study does not specifically investigate the direct relationship between accident types, such as fire/explosion, and watchkeeping schedules on navigating bridges.

3.2. Enhanced Multilevel Association Rule Mining (EMARM)

ARM is a widely used technique in data mining that uncovers frequent itemsets and generates association rules (Feng et al., 2024a). However, traditional ARM technology, when applied to data with multiple states such as navigable waters and wind speed, typically analyses each state independently, making it challenging to capture the overall correlations between these states and other factors comprehensively. To address this issue, this study proposes the EMARM algorithm, an advancement of traditional ARM. The EMARM algorithm aims to extract more complex and comprehensive association rules by integrating multilevel data. Compared to traditional ARM, EMARM can simultaneously consider the combined effects of multiple states, thereby providing a more accurate reflection of correlations in complex datasets. This improvement not only enhances the depth and breadth of the

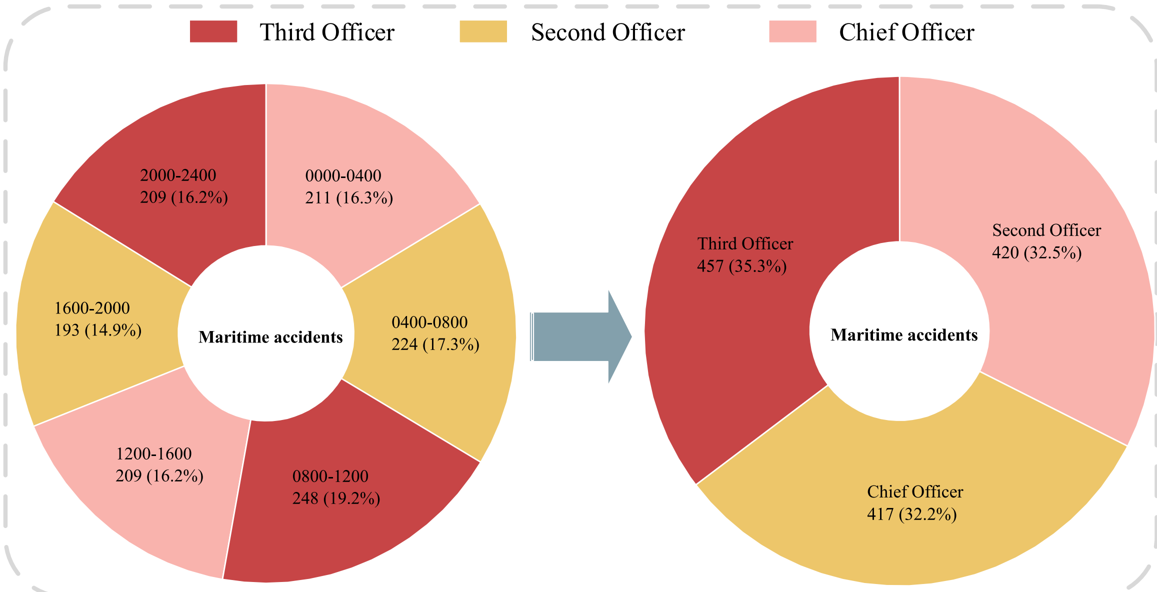

Fig. 3. Distribution of the accident occurrences.

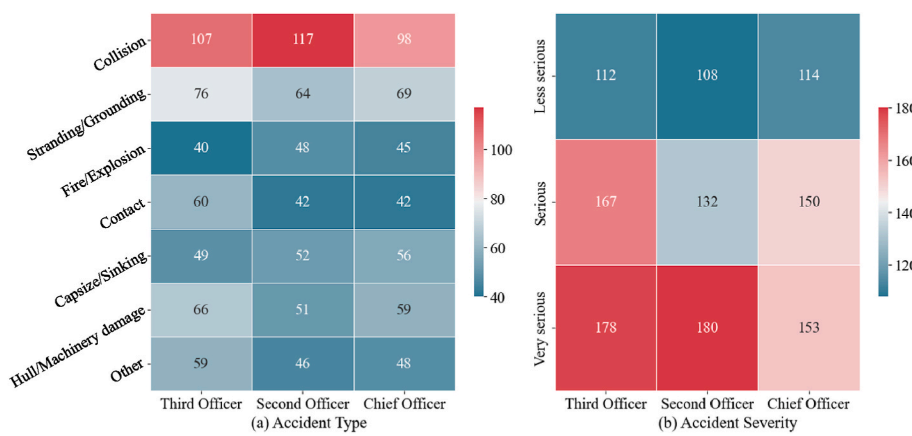

Fig. 4. Accident type and severity distribution.

analysis but also more effectively identifies the key RIFs and potential risks affecting maritime accidents. The formulas and pseudocode are presented in Equation (1) and Table 1, respectively.

Table 1
The pseudocode of EMARM algorithm.

Algorithm 1: Enhanced Multilevel Association Rule Mining algorithm

Input: Dataset, **DS**; Minimum support threshold, **min_sup**; Minimum confidence threshold, **min_ confidence**
Output: EMARs
Begin
Calling Association Rule algorithm (Apriori, FP-Growth, etc.)
Return association rules that satisfy **min_sup**; **min_ confidence** and **lift > 1, AR**
Generate two matrices **CE** and **SE** with Conviction$(E_i \Rightarrow F_j)$ and *Support*$(E_i \Rightarrow F_j)$ as elements, respectively, based on the **AR**
Use Equation (5) to perform scaling nodes operations are performed on C and S based on factors states to form new combined matrices, **EM**
Change the diagonal of **EM** to all Zeros, **EMARM**
Transforming **EMARM** matrix into association rule format
Return EMARs
End

$$EM(E \Rightarrow F) = \sum_i \sum_j \text{Conviction}(E_i \Rightarrow F_j) \times \frac{Support(E_i \Rightarrow F_j)}{\sum_i \sum_j Support(E_i \Rightarrow F_j)} \tag{1}$$

where, E and F represent different RIFs, E_i and F_j denote the various states within RIF E and RIF F, respectively. Conviction$(E_i \Rightarrow F_j)$ indicates the conviction level of E_i to F_j, while $Support(E_i \Rightarrow F_j)$ represents the support for E_i to F_j. $EM(E \Rightarrow F)$ reflects the enhanced multilevel conviction of RIFs E to F, illustrating the degree of influence of the antecedent on the consequent at the overall level of RIFs.

The interpretability of association rules is improved by calculating the conviction between different states and integrating these into a unified metric. Specifically, $EM(E \Rightarrow F)$ computes overall conviction by combining all possible state sets, which reduces the impact of individual or anomalous state sets on the results, thereby providing a more stable and reliable association measure. This approach not only enhances the robustness of association rules but also accurately captures the overall relationships among multi-state factors in complex datasets. This provides a reliable theoretical foundation and data support for subsequent integration with WINGS.

3.3. Weighted Influence Non-linear Gauge System (WINGS)

Maritime accidents are typically not random events but rather result from the interplay of multiple RIFs. The interactions among these RIFs create a complex system. The WINGS methodology is instrumental in identifying key RIFs of maritime accidents and uncovering the dependencies and causal relationships among them (Cao et al., 2024b). Traditionally, the WINGS method relies on expert judgments to determine the influence degrees between factors, which can introduce subjectivity and uncertainty into the analysis. To mitigate these issues, this study adopts a data-driven approach for constructing the WINGS model. The specific process of this method is outlined as follows.

Step 1: Construct the direct influence matrix using the EMARs, as detailed in Equations (2)–(4).

$$D=\begin{array}{c} \\ Ge_1 \\ Ge_2 \\ \vdots \\ Ge_n \end{array}\begin{array}{c} \begin{array}{cccc} Ge_1 & Ge_2 & \cdots & Ge_n \end{array} \\ \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & d_{EF} & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix} \end{array} \tag{2}$$

$$d_{EF}=n_{EF}\times EM(E\Rightarrow F) \tag{3}$$

$$n_{EF}=\begin{cases} 1, \textit{when an association rule exists from E to F} \\ 0, \textit{else} \end{cases} \tag{4}$$

where D represents the direct influence matrix; Ge_i denotes a specific RIF analysed in this study; d_{EF} indicates the degree of influence of RIF E on RIF F; and n_{EF} indicates whether there is a significant influence of RIF E on RIF F, with 1 indicating a significant influence and 0 indicating no significant influence.

Step 2: Normalize the direct influence matrix to obtain the normalized direct influence matrix $NorD$, as calculated using Equations (5)–(8).

$$Np=\frac{1}{\left(\max\left(e_1,e_2,\cdots,e_n\right)^2+\max\left(f_1,f_2,\cdots,f_n\right)^2\right)^{1/2}} \tag{5}$$

$$e_i=\sum_j d_{ij} \tag{6}$$

$$f_i=\sum_j d_{ji} \tag{7}$$

$$NorD=Np\times D \tag{8}$$

where Np is the normalization parameter; e_i indicates the sum of row i of the direct influence matrix; f_i indicates the sum of column i of the direct influence matrix; and $NorD$ denotes the normalized direct influence matrix.

Step 3: Apply the influence transmissibility theory to construct a complete influence matrix CH using the formula provided in Equation (9).

$$CH=\sum_{k=1}^{\infty} NorD^k=NorD\cdot(I-NorD)^{-1}=(t_{EF})_{n\times n} \tag{9}$$

where $\cdot$ denotes the matrix inner product, I represents the unit matrix, and t_{EF} indicates the combined impact of RIF E on RIF F within the complete influence matrix.

Step 4: Utilizing the complete influence matrix, compute the affected degree, influence degree, centrality degree, and reason degree of the RIFs, as well as the weight of each RIF, as shown in Equations (10)–(14).

$$x_E=\sum_F t_{EF} \tag{10}$$

$$y_E=\sum_F t_{FE} \tag{11}$$

$$CD_E=x_E+y_E \tag{12}$$

$$RD_E=x_E-y_E \tag{13}$$

$$WT_E=\frac{\left(CD_E{}^2+RD_E{}^2\right)^{1/2}}{\sum_E\left(CD_E{}^2+RD_E{}^2\right)^{1/2}} \tag{14}$$

where x_E denotes the influence degree of RIF E; y_E denotes the affected degree of RIF E; CD_E denotes the centrality degree of RIF E; RD_E and WT_E denote the reason degree and the weight of RIF E.

3.4. Total Adversarial Hasse Diagram Technology (TAHDT)

Understanding the complex interactions between RIFs in maritime accident research is crucial for enhancing safety management and preventing accidents. HDT is designed to analyse and structure the interactions between elements in complex problems. It focuses on presenting these interrelationships in a structured format to enhance understanding (Dong et al., 2023; Zhang et al., 2023). In practice, HDT and WINGS complement each other in addressing complex problems and system analysis. WINGS focuses on identifying and analysing both direct and indirect influences and interactions between RIFs, while HDT constructs hierarchical models to graphically present the dependencies and structure of these factors. TAHDT enhances traditional HDT by incorporating adversarial game theory to provide a deeper understanding of the influence relationships between RIFs. In this study, the TAHDT method was employed to extract RIFs in both cause- and effect-oriented manners, forming a dyadic directed topology to determine the influence relationships between RIFs. These two extraction methods differ in their hierarchical identification of RIFs: Up-type methods arrange RIFs from top to bottom, while down-type methods arrange them from bottom to top. This hierarchical structure facilitates essential comparisons and validations from different perspectives, making it suitable for analysing complex systems with numerous factors, intricate relationships, and ambiguous structures. In this study, the results from WINGS were used as inputs for TAHDT to leverage the complementary strengths of both methods, thereby enhancing the understanding and analysis of causality within the maritime accident system. The specific process is detailed below.

Step 1: Eliminate less influential relationships in CH using the intercept threshold IT to create the relationship matrix RH. This matrix reflects the strong interaction relationships between RIFs and is calculated as shown in Equations (15)–(19).

$$RH=(rh_{EF})_{n\times n} \tag{15}$$

$$rh_{EF}=\begin{cases} 1, \textit{if } t_{EF}>IT \\ 0, \textit{else} \end{cases} \tag{16}$$

$$IT=AI+\sigma \tag{17}$$

$$AI=\frac{\sum_E(x_E+y_E)}{n^2} \tag{18}$$

$$\sigma=\left(\frac{\sum_E\sum_F(t_{EF}-AI)^2}{n^2}\right)^{1/2} \tag{19}$$

where AI denotes the average degree of influence among RIFs; σ denotes the overall standard deviation of the influence degree among RIFs; and IT denotes the intercept threshold.

Step 2: Using Boolean operations to obtain the reachability matrix, as detailed in Equations (20) and (21):

$$B_1 = RH + I, B_2 = B_1 \odot B_1, B_3 = B_2 \odot B_1, \cdots, B_n = B_{n-1} \odot B_1 \tag{20}$$

$$RM = (h_{EF})_{n\times n} = B_k = B_{k-1} \neq B_{k-2} \tag{21}$$

where RM is the reachability matrix and B_i is the transition matrix in Boolean operations.

Step 3: Develop UP-type and DOWN-type hierarchical models by leveraging the reachability set and the antecedent set, along with their intersection, focusing on causal relationships as outlined in Equations (22)–(24).

$$Rs(Ge_E) = \{Ge_F | h_{EF} = 1\} \tag{22}$$

$$Qs(Ge_F) = \{Ge_E | h_{FE} = 1\} \tag{23}$$

$$Ts(Ge_E) = RS(Ge_E) \cap QS(Ge_E) \tag{24}$$

where $Rs(Ge_E)$ denotes the reachability set of Ge_E, i.e., the set of RIFs with elements equal to 1 in row E of the reachability matrix. $Qs(Ge_F)$ denotes the a priori set of Ge_F, i.e., the set of RIFs with elements equal to 1 in column F of the reachability matrix. $Ts(Ge_E)$ represents the intersection of the reachability set and the antecedent set.

To form an UP-type hierarchy, RIFs are selected from the reachability set $Rs(Ge_E)$, and these RIFs are placed at the surface level when $Rs(Ge_E) = Ts(Ge_E)$. The selected RIFs are then removed from the reachability set. This process creates a new reachability set and a new intersection. Conversely, to form a DOWN-type hierarchy, RIFs are selected from the a priori set $Qs(Ge_F)$, and these RIFs are placed at the entity layer when $Qs(Ge_E) = Ts(Ge_E)$. These RIFs are then removed to create a new a priori set and a new intersection set. This hierarchical process is iteratively applied until all RIFs are exhausted.

Step 4: First, apply the Tarjan algorithm to identify the strongly connected components within the reachability matrix RM (Tarjan and Zwick, 2024). Next, develop the shrinking node matrix RM' based on these identified components. Lastly, generate the skeleton matrix SM by applying the shrinkage equation. The relevant formulas are detailed in Equations (25) and (26):

$$RM \xrightarrow{Tarjan} RM' \tag{25}$$

$$SM = RM' - (RM' - I) \odot (RM' - I) - I \tag{26}$$

Step 5: Finally, develop the DOWN-type and UP-type topology hierarchies using the skeleton matrix SM.

3.5. *Matrices Impacts Croises-Multiplication Appliance Classement (MICMAC)*

Determining the systematic role and influence of each RIF in maritime accident analysis is essential for optimizing safety management strategies. The MICMAC method utilizes matrix multiplication to analyse the influence and dependence among factors in a system. By calculating driving and dependence forces, it clarifies the role and position of each influencing factor within the system (Kaladharan et al., 2024). To verify the reasonableness of the TAHDT model for hierarchical classification of RIFs in maritime accidents, this study employed MICMAC to conduct a detailed analysis of the driving and dependence forces of each RIF. The process is outlined below.

Step 1: Calculate the driving force DF of the RIFs, which is calculated as in Equation (27).

$$DF_i = \sum_{j=1}^{n} a_{ij} \tag{27}$$

where a_{ij} represents the value of the element in the ith row and jth column of the reachability matrix RM, and DF_i denotes the sum of the ith row of RM.

Step 2: Calculate the dependence force RF of RIFs, the formula is as in Equation (28).

$$RF_j = \sum_{i=1}^{n} a_{ij} \tag{28}$$

where RF_j represents the sum of the jth column of RM.

4. Results and discussion

4.1. *EMARM analysis*

This study identifies potential associations among RIFs using the EMARM algorithm. Unlike traditional ARM, which examines associations at the level of individual states, this study analyses them at the overall level of factors. It is important to note that the choice of EMARM thresholds significantly impacts the quality of association rules (Feng et al., 2024a; Sun, 2024). In this study, after several experiments, the minimum support threshold and minimum confidence threshold were set to 0.1 and 0.75, respectively. Additionally, to ensure that each antecedent and consequent term represents only one RIF, the maximum restriction length was set to 2.

In this study, the EMARM algorithm was used to mine maritime accident data from the chief officer 's watch, the second officer's watch, and the third officer 's watch, resulting in 553, 570, and 550 EMARs, respectively. The size of the enhanced multilevel conviction level reflects the strength of the association rules: the higher the conviction ranking, the stronger the interaction between two neighbouring RIFs. The top 10 EMARs are presented in Table 2.

In this study, the data presented in Table 2 shows that some RIFs are interrelated. It is worth noting that there is a correlation among SC (Seafarers' certificates), SM (Ship manning), and SSC (Ship's certificates) during the third officer 's watch. Similarly, during the second officer 's watch, there was a correlation among MV (Administration's violation of supervision), MR (Administration's regulations), and HEB (Education background). During the chief officer's watch, there is a bidirectional correlation between MV (Administration's violation of

Table 2
Top 10 EMARs ranked by conviction values.

DP	N	A	C	Cv	N	A	C	Cv
Third officer	1	SE	SC	10.54	6	EF	HC	8.32
	2	SG	SC	9.83	7	EF	SM	8.06
	3	SC	SSC	9.57	8	HTS	HC	7.89
	4	HTR	HC	9.32	9	SM	SSC	6.53
	5	MC	SSC	8.77	10	SM	SC	6.21
Second officer	1	MT	SM	10.93	6	MV	HEB	8.27
	2	ET	HC	10.32	7	HTS	SM	7.83
	3	SE	SC	9.94	8	EV	SS	6.65
	4	MV	MR	9.52	9	MC	SSC	6.21
	5	SE	SM	8.63	10	HEB	MR	5.95
Chief officer	1	SC	SSC	10.37	6	SE	HC	8.23
	2	HO	HC	9.63	7	SSC	SM	7.64
	3	MV	MR	9.44	8	MR	MV	7.13
	4	HTS	HC	9.21	9	MD	SSC	6.85
	5	SE	SM	8.79	10	MD	SM	6.18

Note: DP indicates different watchkeeping periods; N indicates serial number; A indicates antecedent; C indicates consequent; Cv indicates conviction values.

supervision) and MR (Administration's regulations). From a practical perspective, these interconnections are highly credible. For example, MV and MR both pertain to regulatory practices and procedures, making their bidirectional correlation plausible and intuitive in the context of shipping safety management.

Fig. 5 displays the comparative results of EMARs data streams across different watchkeeping periods, visualizing the linkage relationships between various itemsets from a holistic perspective. The differences in the linkage of RIFs during different watchkeeping periods are evident from the variations in node area. RIFs such as SC (Seafarers' certificates), SM (Ship manning), and MSS (The company's safety management) have the largest node areas during the third officer's watch. RIFs such as MR (Administration's regulations), HEB (Education Background), and SC (Seafarers' certificates) have the largest node areas during the second officer's watch. RIFs such as MR (Administration's regulations), HEB (Education background), and SSC (Ship's certificates) have the largest node areas during the chief officer's watch. All of these RIFs exhibit significant linkage effects in accidents. Analysing these RIFs provides an in-depth understanding of the risk dynamics associated with different positions in maritime operations and offers valuable guidance for developing targeted safety management strategies.

4.2. Causality analysis based on WINGS

This section examines the causal connections among RIFs by evaluating reason degree, centrality degree, and weight values. First, the direct influence matrix *D* is constructed based on EMARM and Equation (2). This matrix *D* is then normalized as per Equations (5)–(8), resulting in the normalized direct influence matrix *NorD*. Subsequently, the comprehensive influence matrix *CH* is calculated using Equation (9). The final step involves plotting the causality and weight distributions for each RIF based on their reason degree, centrality degree, and weight values.

The centrality degree (CD) indicates the significance and impact of each RIF in a maritime accident. In contrast, the reason degree (RD) determines whether the RIF functions as an influence initiator or a recipient. The weight (WT) integrates aspects of both centrality degree and reason degree, adjusting for the effects of positive and negative values in reason degree relationships to more accurately represent each RIF's overall importance. Through detailed analyses of centrality degree, reason degree, and weight, this study provides a thorough understanding of the dynamics driving maritime accidents and the interconnections among RIFs. These findings are crucial for formulating strategies to prevent maritime accidents, reduce their frequency, and improve overall maritime safety.

The causal distribution of each RIF is shown in Fig. 6. The five RIFs with the most significant effects during the third officer's watchkeeping period are MSS (The company's safety management), MV (Administration's violation of supervision), SC (Seafarers' certificates), SM (Ship manning), and SSC (Ship's certificates). Table 3 presents the RIFs with higher centrality degree values for maritime accidents during other watchkeeping periods. Additionally, by analysing the weight, this study further identifies the criticality of these RIFs across different watchkeeping periods. As shown in Fig. 7, MSS (The company's safety management), MV (Administration's violation of supervision), SC (Seafarers' certificates), SM (Ship manning), and SSC (Ship's certificates) ranked highest in the weight values of RIFs during the third officer's watch. Table 3 also presents the RIFs with higher weight values for maritime accidents during other watchkeeping periods. This data confirms a positive correlation between the weight and centrality degree.

The reason degree (RD) was analysed to ascertain the causal dynamics among RIFs. A positive RD value (>0) indicates that the RIF acts as a causative element influencing other RIFs, while a negative RD value (<0) signifies that the RIF is an outcome factor influenced by other RIFs. As shown in Fig. 6, RIFs such as ED (Depth-draft ratio), SA (Ship's age), and EV (Visibility) exhibit positive reason degree values during the third officer's watch. Table 4 presents the RIFs with higher reason degree values for maritime accidents during other watchkeeping periods, indicating their dominant influence on other RIFs in those periods. In contrast, RIFs such as SM (Ship manning), SC (Seafarers' certificates), and HC (Communication problem) show negative reason degree values during the third officer's watch.

When considered collectively, outcome factors that possess high centrality degree values typically assume a critical role in the transmission of risk within the system. Therefore, these RIFs should be prioritized. The analysis of centrality degree reveals significant differences in key RIFs affecting maritime accidents across the watchkeeping periods of the third officer, second officer, and chief officer. Identifying these heterogeneous RIFs for each watchkeeping period is essential for developing targeted maritime accident prevention strategies. For example, during the third officer's watch, critical RIFs include MSS (The company's safety management), MV (Administration's violation of supervision), and SC (Seafarers' certificates). During the second officer's watch, important RIFs are HEB (Education background), SM (Ship manning), and ES (Sea state). For the chief officer's watch, the critical RIFs are MR (Administration's regulations), SPF (PSC/FSC inspection), and HC (Communication problem). These above RIFs are heavily influenced by other factors and given their high centrality degree, any changes within them can have a wide-ranging impact on the progression of a maritime accident. Consequently, it is essential to give particular attention to these RIFs to prevent their negative effects from being

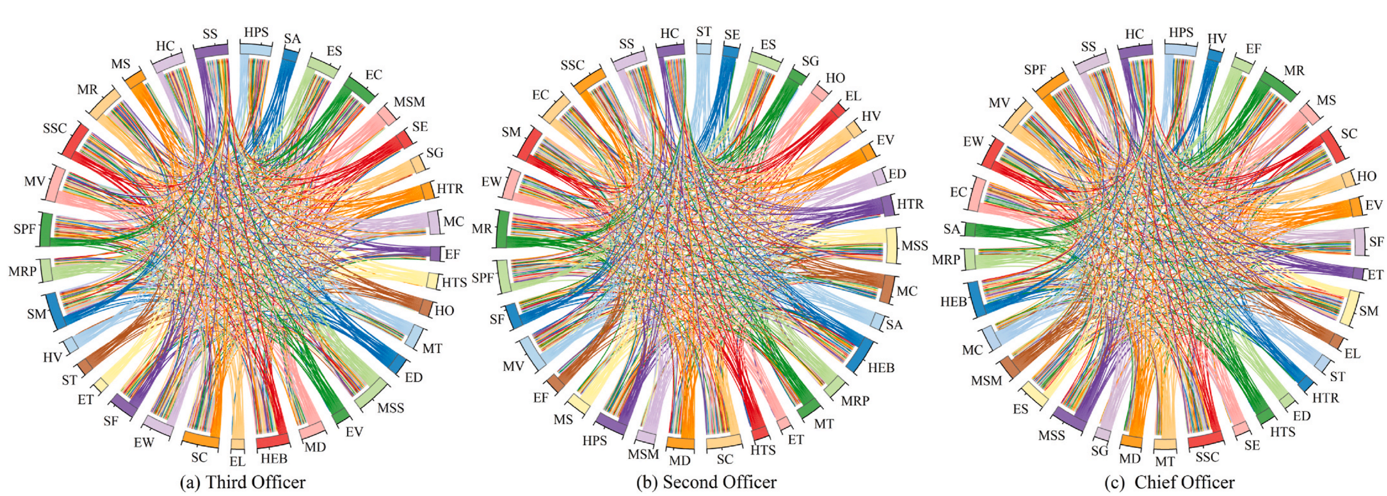

Fig. 5. The comparison result of EMARs data flow.

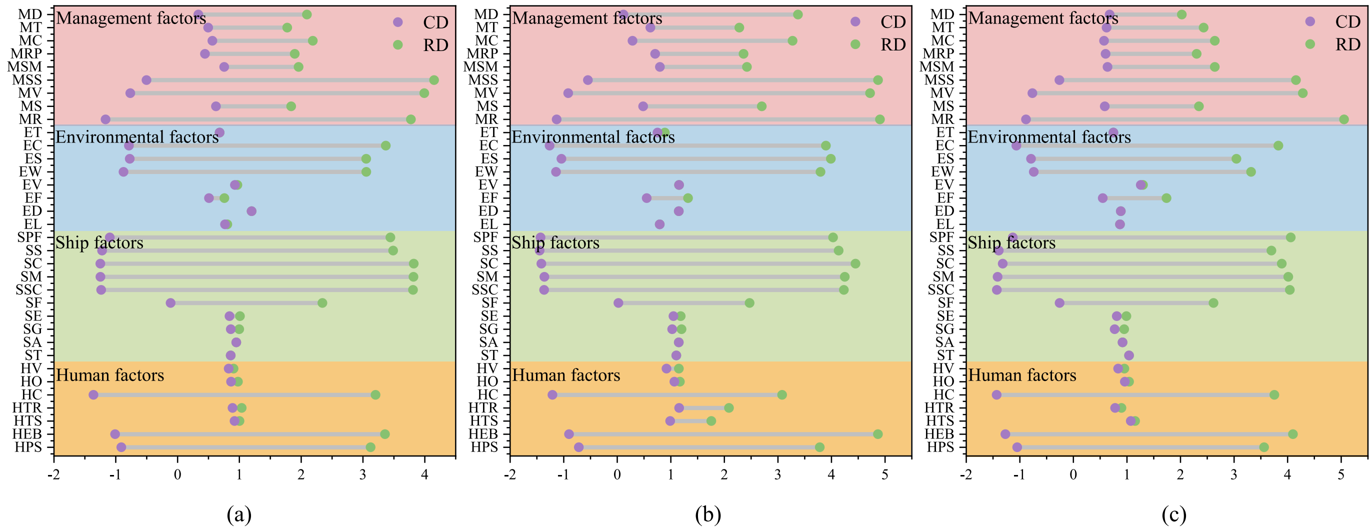

Fig. 6. The causal diagram of RIFs. (a) Third Officer, (b) Second Officer, and(c) Chief Officer.

Table 3
The RIFs with large CD and WT values.

Watchkeeping period	RIFs (CD)	RIFs (WT)
Second Officer	MR (Administration's regulations), MSS (The company's safety management), HEB (Education background), MV (Administration's violation of supervision) and SC (Seafarers' certificates)	MR (Administration's regulations), HEB (Education background), MSS (The company's safety management), MV (Administration's violation of supervision) and SC (Seafarers' certificates)
Chief Officer	MR (Administration's regulations), MV (Administration's violation of supervision), MSS (The company's safety management), HEB (Education background) and SPF (PSC/FSC inspection)	MR (Administration's regulations), MV (Administration's violation of supervision), HEB (Education background), SSC (Ship's certificates) and SM (Ship manning)

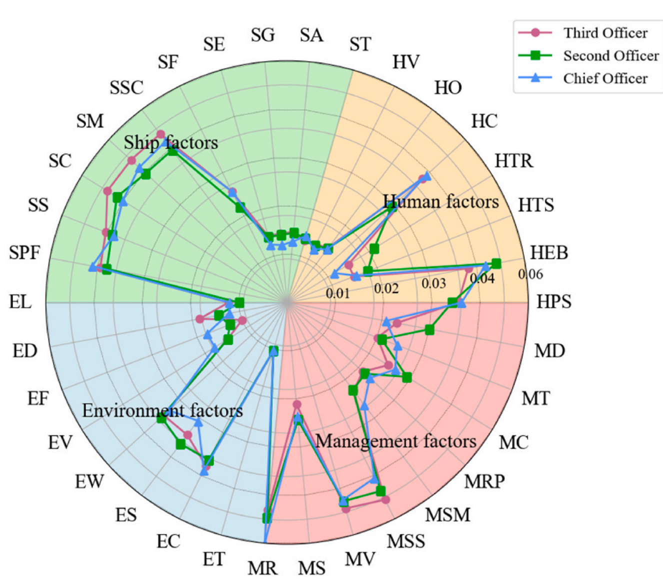

Fig. 7. Weight distribution of RIFs.

Table 4
The RIFs with large RD values.

Watchkeeping period	Causal factors (RD > 0)	Outcome factors (RD < 0)
Second Officer	HTR (Time in present rank), EV (Visibility) and SA (Ship's age)	SC (Seafarers' certificates), SPF (PSC/FSC inspection) and SS (Seaworthiness)
Chief Officer	EV (Visibility), HTS (Time at sea) and ST (Ship type)	SM (Ship manning), SSC (Ship's certificates) and HC (Communication problem)

amplified and worsening the severity of the accident.

4.3. Hierarchical structure analysis based on TAHDT

This section examines the interdependent or coupling relationships among RIFs using the adversarial hierarchical topology map. First, an intercept threshold is applied to *CH*, to filter out less significant influence relations, resulting in the formation of *RH*. Second, Boolean operations are performed using Equations (20) and (21) to obtain *RM*. The *SM* is then obtained by simplifying the points and edges within *RM*. Based on this calculation, the hierarchical structure of maritime accident RIFs can be delineated through DOWN-type and UP-type extractions. Finally, further division of hierarchical elements is performed to construct the confrontation hierarchy topology. Then, the UP/DOWN-type confrontation hierarchy topology characteristics for the third officer's watchkeeping period are illustrated in Fig. 8, while the topology diagrams for other watchkeeping periods are detailed in Figures B.1 and B.2 in Appendix B.

The UP-type and DOWN-type confrontation hierarchy topology maps represent outcome-oriented and cause-oriented hierarchies, respectively. In these maps, the reachability relationships between RIFs involved in a maritime accident are illustrated using directed line segments. Rectangular boxes within the diagrams indicate the formation of loops, indicating that mutually reachable relationships between RIFs create strong connectivity components. Additionally, RIFs positioned lower in the hierarchy are more foundational, while those higher up are more direct. The confrontation hierarchy topology reveals that RIFs related to maritime accidents during the third officer's, second officer's, and chief officer's watches are categorized into five levels, from L1 to L5. RIFs at level L1 are surface layer factors (S-RIFs), those at levels L2 to L4 are middle-level factors (M-RIFs), and those at level L5 are underlying factors (U-RIFs).

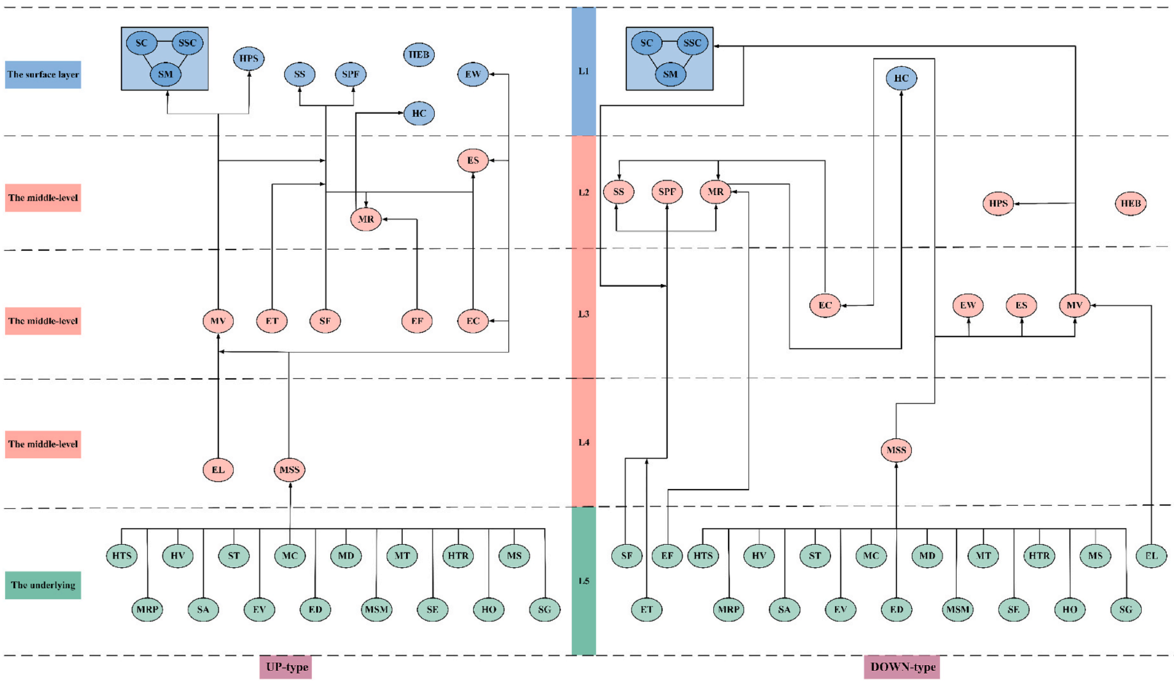

Fig. 8. The causal diagram of RIFs (Third Officer).

(1) The results of loop analysis

Loops, often referred to as strongly connected components, are detected and combined through the application of the Tarjan algorithm (Tarjan and Zwick, 2024). The study identified several such strongly connected components, including SSC/SC/SM during the third officer's watch, MV/MR/HEB during the second officer's watch, and MV/MR during the chief officer's watch. Each strongly connected component was treated as a single node for further analysis. Strongly connected components reflect a high level of interdependence and interaction among the RIFs they include. For example, the bidirectional correlation between MV and MR during the chief officer's watch is discussed in the EMARM results in Section 4.1. Similarly, SSC, SC, and SM during the third officer's watch, as well as MV, MR and HEB during the second officer's watch exhibited significant correlations, as shown in Table 2. These findings further confirm the consistency of the analyses. From a practical perspective, the RIFs within these strongly connected components demonstrate significant interdependence in the occurrence of maritime accidents. Specifically, SSC, SC and SM are all factors related to the ship's internal conditions. Thus, a failure in any of these components indicates a potential influence on accident occurrence due to the ship's own factors. Similarly, issues with any of MV, MR or HEB suggest that the ship may be unseaworthy. Consequently, it is vital to carefully observe these cyclically interconnected strongly connected components, as a failure in any one RIF can trigger a cascade of failures among related RIFs, thereby increasing the likelihood of an accident.

(2) The results of isolated factors analysis

From Fig. 8, it is evident that HEB (Education background) is isolated within the maritime accident system during the third officer's watch, showing no directional connections with other RIFs. This indicates that HEB (Education background) does not interact readily with other RIFs. Consequently, HEB (Education background) directly influences the development of maritime accidents and is less likely to interact in conjunction with other RIFs. As a factor related to the crew's educational background, HEB (Education background) can significantly influence the skill level and expertise of crew members, thereby impacting their decision-making and behaviour during sea voyages (Mejsner et al., 2024). For instance, a strong educational background can enhance the crew's ability to handle emergencies and recognize risks, thus reducing the likelihood of maritime accidents. Moreover, the isolated nature of HEB (Education background) suggests that improvements or adjustments should be tailored specifically through targeted training strategies and education programs, rather than relying solely on changes in other RIFs. To effectively mitigate the risks associated with inadequate educational backgrounds among crew members, customized training programs should be developed. By implementing such tailored educational initiatives, third officers can acquire the essential skills and knowledge for critical operations, thereby significantly reducing the potential risk of maritime accidents. This approach not only strengthens individual competence but also enhances the overall efficiency and safety of the ship's operational team.

(3) The results of surface layer factors analysis

S-RIFs represent the most immediate factors influencing maritime accidents, located at the surface level of the system. They do not project directional lines outward but are solely impacted by other RIFs. As illustrated in Fig. 8, during the third officer's watch, both UP-type and DOWN-type RIFs include SSC (Ship's certificates), SC (Seafarers' certificates), SM (Ship manning), and HC (Communication problem). These RIFs are positioned at the surface level, indicating they may be early indicators of potential maritime accidents during the third officer's watch. Additionally, the UP-type RIFs include HPS (Physical and mental state), SS (Seaworthiness), SPF (PSC/FSC inspection) and EW (Wind force). These factors also play a critical role in shaping the conditions that may lead to accidents. When ship certificates are problematic and crew certificates are unqualified, this poses significant threats to the legality and safety of ship operations. In this case, even if a ship is manned with a sufficient number of crew members, it is difficult to compensate the lack of qualified personnel, which increases the likelihood of communication problems during ship operations. As illustrated in Figure B.1 of Appendix B, the maritime accident hierarchy topology during the second officer's watch identifies both UP and DOWN types at this level. These include SSC (Ship's certificates), SC (Seafarers' certificates), SM (Ship manning), EW (Wind force), SS (Seaworthiness), SPF (PSC/FSC inspection), ES (Sea state), and EC (Current speed). This indicates that these RIFs may be the earliest signs of a maritime accident during the second officer's watch. Additionally, the UP type also includes HC (Communication problem). The seaworthiness of a ship can be compromised under adverse conditions such as rough seas and fast currents. When these factors are combined with communication problems, the transmission of crucial information may be disrupted or delayed, thereby increasing the difficulty of responding to emergencies. As illustrated in Figure B.2 of Appendix B, the maritime accident hierarchy during the chief officer's watch identifies both UP and DOWN types including SSC (Ship's certificates), SC (Seafarers' certificates), SM (Ship manning), SS (Seaworthiness), and HC (Communication problem) at this level. This suggests that these RIFs may be the earliest indicators of a maritime accident during the chief officer's watch. Additionally, the UP type includes ES (Sea state) and HPS (Physical and mental state). When the chief officer is in poor physical and mental condition and the ship faces rough sea conditions, communication difficulties may be exacerbated, thereby reducing the safety of the ship's navigation.

Due to the variations in S-RIFs across different watchkeeping periods, it is essential to implement targeted risk control measures for each period. Prioritizing the management of these S-RIFs is crucial in maritime risk management and prevention strategies. Effective control measures should aim to disrupt interactions between these S-RIFs to minimize their potential impacts early in an accident.

(4) The results of middle-level factors analysis

M-RIFs are influenced by U-RIFs and, in turn, can also affect S-RIFs. While their impact is not as direct as that of S-RIFs, M-RIFs are crucial for connecting various aspects of accident RIFs. They serve an important role in bridging the gap between U-RIFs and S-RIFs, facilitating the flow of influence throughout the risk system. In the accident hierarchy topology of the maritime during the third officer's watch, both UP and DOWN types identify factors such as ES (Sea state), MR (Administration's regulations), EC (Current speed), MV (Administration's violation of supervision), and MSS (The company's safety management system) at the intermediate level. Both UP/DOWN-type hierarchical topologies of maritime accidents during the third officer's watch indicate that deficiencies in MR (Administration's regulations) can lead to HC (Communication problem). For instance, if regulations do not explicitly mandate the use of specific communication protocols or equipment in particular situations, it can result in poor information transmission or misunderstandings during emergencies. This issue is particularly critical during the third officer's watch, as the third officer is the executor to communication and operational roles in emergency response scenarios. In the maritime accident hierarchy topology during the second officer's watch, both UP-type and DOWN-type classifications identify HEB (Education background), MR (Administration's regulations), MV (Administration's violation of supervision), HPS (Physical and mental state), and MSS (The company's safety management system) as intermediate-level factors. From these hierarchical topologies, it is evident that during the second officer's watch, RIFs related to educational background and management, such as HEB, MR, and MV, may not directly cause maritime accidents. However, they can significantly influence the ship's seaworthiness (SS), potentially placing the ship in a hazardous state. In the maritime accident hierarchy topology during the chief officer's watch, both UP-type and DOWN-type classifications identify EC (Current speed), SPF (PSC/FSC inspection), HEB (Education background), EW (Wind force), MR (Administration's regulations), MV (Administration's violation of supervision), and MSS (The company's safety management system) as intermediate-level factors. These hierarchical topologies indicate that during the chief officer's watch, RIFs such as EC, SPF, HEB, and EW influence maritime accidents by impacting SM (Ship manning). Specifically, current speed and wind conditions can affect the ship's manoeuvring and speed, thereby increasing the workload on the pilot. Additionally, the results of port state/flag state inspections can alter the ship's operational plans, resulting in additional workload and stress on the crew, which may increase the risk of manoeuvring errors. Educational background is crucial for a ship's pilot; inadequate education can reduce the accuracy of manoeuvres, thereby increasing the likelihood of accidents. These RIFs interact with each other to influence the pilot's skills, collectively constituting the risk factors that can trigger maritime accidents.

Considering the differences in M-RIFs during various watchkeeping periods, it is essential to implement targeted risk control measures. By effectively managing M-RIFs, we can interrupt the transmission paths between these factors, thereby enhancing overall maritime safety.

(5) The results of underlying factors analysis

U-RIFs are the most central RIFs affecting maritime accidents and are positioned at the deepest level of the system. They influence other RIFs through directed edges but are not affected by any other RIFs. In the maritime accidents hierarchy topology for each watchkeeping period, both UP and DOWN types define EV (Visibility), MSM (The company's safety management), MRP (Rectification of the company's problems), MT (Company training) and MC (Company safety culture) at this level. These RIFs, which encompass visibility conditions and well-established management systems, align with the characterization of U-RIFs as deeply embedded and challenging to change swiftly. Their profound impact on the potential risk of maritime accidents underscores the need for comprehensive and long-term management strategies. The hierarchical topology for each watchkeeping period reveals that U-RIFs in maritime accidents across all watchkeeping periods exert their influence through MSS (The company's safety management system). This underscores the critical role of a company's safety management system as the central mechanism for preventing and responding to maritime accidents. It is important to note that EV (Visibility), MSM (The company's safety management), and MC (Company safety culture) also influence ES (Sea state) during the chief officer's watch. This interaction highlights the systemic and integrated nature of maritime safety management. EV serves as a critical indicator of sea conditions. MSM pertains to the ship's operation and management, including the development and implementation of strategies for various sea states. Meanwhile, MC impacts the crew's safety awareness and behaviour, which affects their perception and response to sea conditions. Given that sea state is dynamic and unpredictable, controlling the influence of EV, MSM, and MC can enhance a ship's adaptability to challenging conditions, thereby reducing accident risks and ensuring the safety of vessels and crews.

Controlling U-RIFs generally leads to long-term improvements in safety. Implementing tailored risk control measures for each watchkeeping period—third officer, second officer, and chief officer—is essential. Given that U-RIFs are foundational factors influencing maritime accidents, effective management of these factors will have lasting positive effects, ensuring ongoing maritime safety. It is important to note that controlling U-RIFs focuses more on preventive strategies rather than merely addressing accidents reactively. This proactive approach helps establish a stable and sustainable safety management system, better equipped to handle the complexities and uncertainties of the maritime environment.

4.4. Classification analysis based on MICMAC

In this study, RIFs of maritime accidents are categorized using MICMAC to analyse their interrelationships. Relationships among RIFs are identified based on their driving force and dependence force characteristics. RIFs with greater driving force have a significant impact on other RIFs, while RIFs with higher dependence force are more influenced by other RIFs. Based on the correlation calculation of the reachability matrix, all 34 RIFs are classified into four distinct quadrants: linkage, dependent, autonomous, and independent, as illustrated in

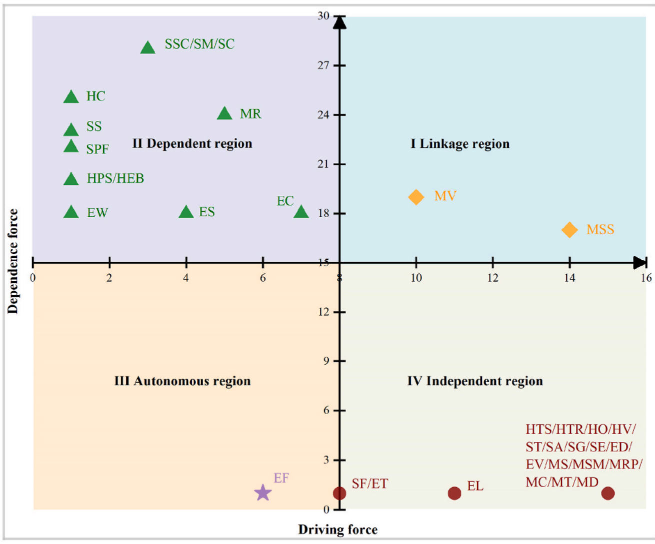

Fig. 9. Classification chart of RIFs (Third Officer).

Fig. 9.

(1) Linkage cluster

Quadrant I in Fig. 9 represents a linkage cluster where RIFs exhibit both strong driving force and high dependence force. This means that these RIFs not only have a significant impact on other RIFs but are also highly influenced by them (Costa et al., 2024). As a result, they play a critical role in the occurrence of maritime accidents due to their central position and interactivity within the system. As illustrated in Fig. 9, during the third officer's watch, the linkage cluster comprises MV (Administration's violation of supervision) and MSS (The company's safety management system). Figure B.3 in Appendix B reveals that during the second officer's watch, the linkage clusters encompass MV (Administration's violation of supervision), MSS (The company's safety management system), MR (Administration's regulations), HEB (Education background), and HPS (Physical and mental state). Figure B.4 in Appendix B indicates that during the chief officer's watch, the linkage clusters include MV (Administration's violation of supervision) and MR (Administration's regulations). This type of RIF is highly unstable because any control measures applied may induce feedback effects that could influence the occurrence of maritime accidents. Specifically, the RIFs involved in the linkage clusters for each watchkeeping period are management factors or crew background factors that are difficult to alter in the short term. Consequently, to mitigate the risk of maritime accidents by controlling these RIFs, it is essential to monitor them throughout the entire voyage-before, during, and after. Implementing such monitoring measures can facilitate the timely identification of potential RIFs and enable the adoption of appropriate preventive and intervention strategies to ensure the safety of the ship and the well-being of the crew.

(2) Dependent cluster

Quadrant II represents a dependent cluster characterized by RIFs with low driving force and strong dependence force. These RIFs are highly susceptible to the influence of other cluster RIFs and play a reactive role within the accident system (Costa et al., 2024). During the third officer's watch, the dependent clusters include RIFs such as HC (Communication problem), HPS (Physical and mental state), HEB (Education background), MR (Administration's regulations), EW (Wind force), and ES (Sea state). During the second officer's watch, the dependent clusters include HC (Communication problem), SSC (Ship's certificates), SM (Ship manning), EW (Wind force), ES (Sea state), and other RIFs. During the chief officer's watch, the dependent clusters include HC (Communication problem), HPS (Physical and mental state), HEB (Education background), EW (Wind force), ES (Sea state), and additional RIFs. Among these, MR (Administration's regulations) only appeared in the dependent cluster during the third officer's watch. This suggests that the third officer may need to more closely adhere to and consider government regulatory requirements while on watch. This may indicate that third officers rely more on external regulations and administrative requirements to ensure operational compliance, especially when dealing with complex tasks or unexpected situations. It is crucial for third officers to ensure that all operations comply with established regulatory standards (Shi et al., 2024a). Therefore, enhancing the third officer's understanding and enforcement of administrative regulations is essential for ensuring compliance and the safety of ship operations. Conversely, Wind force (EW) and Sea state (ES) appear in the dependent clusters for all three periods, indicating their significance across all watchkeeping periods. However, it is essential to clarify that while EW and ES are classified within the dependent cluster, this categorization does not suggest that they are inherently influenced by other RIFs from different clusters. Instead, their impact is highly contingent on the interaction with other RIFs, particularly those from human, operational, and environmental domains. Specifically, the magnitude of their effect on vessel safety is susceptible to modulation by other factors within the system. In this sense, although these factors exhibit a dependent nature, they can substantially amplify the effects of other RIFs under certain conditions. For instance, when combined with human factors such as physical and mental state, ship characteristics, or operational practices, wind force and sea state can act as amplifiers, exacerbating the likelihood of accidents. Therefore, while EW and ES are primarily dependent, their potential to act as catalysts in accident escalation—by magnifying the impact of other contributing factors—must be carefully considered in accident causation analysis. This dual role of wind force and sea state, as both dependent factors and amplifiers, underscores the importance of their inclusion in comprehensive safety assessments and accident prevention strategies. The strong dependence of these RIFs in the clusters highlights the need to manage their impact on ship navigation by controlling other RIFs. These factors are crucial because the status and operation of other RIFs significantly influences them. Thus, it is necessary to closely monitor these RIFs and take appropriate precautions to ensure safety and stability during ship navigation.

(3) Autonomous cluster

Quadrant III represents an autonomous cluster characterized by RIFs with lower driving force and dependence force. These RIFs have a relatively weak impact on maritime accidents and primarily function as intermediaries between different RIFs (Costa et al., 2024). During the third officer's watch, the autonomous cluster consists solely of EF (Fairway width/ship length). During the second officer's watch, no autonomous clusters are present, indicating that all RIFs may significantly impact the safety and stability of the ship during this period. In contrast, the chief officer's watch includes autonomous clusters comprising ES (Sea state), EW (Wind force), and SF (Flag state). Although these RIFs have a less direct impact on maritime accidents, they remain important factors to consider and monitor during ship operations. For instance, the combined effects of sea state and wind can influence the stability and manoeuvrability of a ship during the chief officer's watch. Similarly, the level of flag state regulation affects the safe operation of a ship and the enforcement of international regulations.

(4) Independent cluster

Quadrant IV represents an independent cluster characterized by RIFs that are strongly driving force and less dependence force. These RIFs exert a significant impact on the RIFs of other clusters (Costa et al., 2024). During the third officer's watch, the independent cluster includes RIFs such as HTS (Time at sea), HTR (Time in present rank), and HO (Operational error). Similarly, during the second officer's watch, the independent cluster includes RIFs such as HV (Violation operation), ED (Depth-draft ratio (h/d)), and ET (Traffic density). During the chief officer's watch, the independent cluster includes RIFs such as EL (Location), HV (Violation operation), and MT (Company training). These RIFs have a critical impact on maritime accidents, and managing them is crucial for preventing such accidents. This aligns with the factor hierarchy topology in the TAHDT model, further validating the consistency between these analytical approaches.

5. Implications

5.1. Theoretical implications

The novel multidimensional analytical model proposed in this study enables the analysis of mutual and hierarchical relationships among RIFs related to maritime accidents across different watchkeeping periods. Firstly, this study effectively identifies and extracts the key features and common links among RIFs related to maritime accidents using the EMARM algorithm. Secondly, it determines both direct and indirect causal relationships between maritime accident RIFs for each watchkeeping period through WINGS analysis. Subsequently, two types of adversarial hierarchical topologies of maritime accident RIFs for each watchkeeping period are derived using the TAHDT analysis, which includes detailed examinations of U-RIFs in the essential layer, M-RIFs in the intermediate layer, and S-RIFs in the surface layer. Finally, MICMAC analysis reveals the role and position of maritime accident RIFs within the system for each watchkeeping period. Based on the results of the analyses, key RIFs associated with maritime accidents during the watchkeeping periods of third, second, and chief officers can be identified. Targeted measures can then be implemented to manage these RIFs effectively and reduce the likelihood of accidents. This study provides a comprehensive identification method of these critical RIFs and recommends specific strategies for their control. The findings offer valuable theoretical support for maritime safety management, serving as a crucial support for preventing maritime accidents and mitigating associated risks.

The empirical results further validate the interconnections between the four approaches presented in Section 4, demonstrating significant consistency and complementary relationships among them. Specifically, there is a strong correlation between the associations identified in EMARM and the connectivity components highlighted in TAHDT. Additionally, a comparison of the results from WINGS, TAHDT, and MICMAC reveals a significant relationship between the centrality degree (RD) of RIFs and their positions within the hierarchical tiers. When RD is larger than 0, a higher RD of RIFs corresponds to a lower position within the adversarial hierarchy topology, indicating a stronger causal attribute. Conversely, when RD is less than 0, a lower RD of RIFs is associated with a higher position in the adversarial hierarchy topology, signifying a stronger consequence attribute. However, this study did not find a significant correlation between the centrality degree (CD) of RIFs and their hierarchical divisions. This lack of correlation may result from the fact that the CD of RIFs is based on their influence on and by other attributes, which diminishes their causal attributes and weakens their relationship with the adversarial hierarchical topology that represents causal pathways. This study also revealed that the causal relationships of RIFs derived from the WINGS and TAHDT methods are mutually supportive. This conclusion is corroborated by comparing the adversarial hierarchy topology from the TAHDT analysis with the RIF clusters classified by the MICMAC method. Specifically, the surface layer RIFs (S-RIFs) from TAHDT are consistently found in the second quadrant (Dependent Cluster), while most of the essential layer RIFs (U-RIFs) are situated in the fourth quadrant (Independent Cluster). Additionally, the strongly connected components in the middle layer align precisely with the first quadrant (Linkage Cluster), as illustrated in Figures B.1 and B.3 of Appendix B. Isolated RIFs, such as HEB during the third officer's watch, are positioned in the third quadrant (Autonomous Cluster). This consistency is further validated by the alignment of MICMAC results with the TAHDT adversarial hierarchy topology analysis, confirming the logical coherence of the causality between RIFs.

5.2. Practical implications

Section 4 highlights significant differences in key RIFs across different watchkeeping periods. These variations are likely linked to the specific operational environment, crew work habits, and physiological factors during each period. The risks encountered by third, second, and chief officers during their respective watchkeeping periods have distinct characteristics and challenges, necessitating tailored management strategies and preventive measures to mitigate accident risks.

(1) **The strategies for third officer's watchkeeping period:** Management and human factors exhibit a significant influence during the third officer's watchkeeping period, likely because third officers typically have less work experience. Consequently, when faced with complex tasks or emergencies, they often depend on the company's robust safety management system and sufficient crew support. Studies have demonstrated that third officers are more prone to operational errors in high-pressure environments due to their limited experience and emergency response capabilities (Choi, 2022; Yoshida et al., 2021). Therefore, recommendations for third officers should emphasize enhancing operational training and daily supervision to ensure adherence to standard operating procedures, thereby reducing human error and improving operational safety. Additionally, crew health management programs, such as regular physical check-ups, mental health counselling, and vocational skills training, can effectively enhance crew professionalism and their ability to handle unexpected situations (Choi, 2022). The development of a safety culture is also vital, as it not only fosters good operational habits among third officers but also strengthens their safety awareness, ultimately reducing the risk of accidents (Yoshida et al., 2021).

(2) **The strategies for second officer's watchkeeping period:** Second officer's watchkeeping period is primarily influenced by fatigue and physiological conditions, particularly during late-night watch, when crew biorhythms decline, potentially impairing concentration and decision-making ability (Shi et al.). Fatigue is a critical factor influencing the safety of ship operations, particularly in complex navigational environments, where cognitive decline and increased mental load due to fatigue can significantly elevate the risk of accidents (Yang et al., 2023). Therefore, enforcing strict adherence to administrative regulations to ensure operational standardization and compliance is a crucial measure for effectively safeguarding ship safety in conditions of fatigue. Additionally, educational background plays a crucial role, as crew members with advanced specialized knowledge and skills are better equipped to maintain resilience and effectively handle emergencies while fatigued (Mejsner et al., 2024). Therefore, this study recommends strengthening the enforcement of administrative regulations, ensuring operational standardization, and prioritizing the education and training of crew members during the second officer's watchkeeping period to enhance their emergency response capabilities under fatigue.

(3) **The strategies for chief officer's watchkeeping period:** The chief officer's watchkeeping period is more influenced by external environmental factors and the level of management. The chief officer is typically responsible for the overall supervision

and management of the deck department. His extensive experience and high job level enable him to make efficient and strategic decisions in complex environments. However, as workload increases, the chief officer's reaction time may slow when faced with emergencies, potentially impacting the timeliness of the response. Therefore, ensuring strict adherence to administrative regulations and operational protocols to maintain a high level of responsiveness during emergencies is a critical measure for ensuring safety (Uğurlu et al., 2022). Additionally, the chief officer is responsible for the ship's external reviews and regulatory matters, requiring strong compliance management skills. Particularly during port state or flag state inspections, the ship's compliance directly impacts the inspection outcomes. Given these responsibilities, it is essential to ensure that the chief officer possesses the ability to oversee the broader situation and efficiently manage regulatory affairs to guarantee the safe operation of the ship.

In summary, to effectively reduce the risks of maritime accidents, targeted prevention and control measures should be developed based on the key RIFs identified in this study. By integrating multiple analytical methods, this study uncovers the hierarchical relationships and causal links between RIFs across different watchkeeping periods. This theoretical model not only enhances the understanding of the causes of maritime accidents but also provides clear guidance for risk management in actual operations. Applying these findings can lead to the development of refined operational protocols and training programs for all crew types, optimize ship management processes, and improve overall safety management. The results offer robust theoretical support and empirical evidence for maritime safety management, risk prevention, and emergency response, with significant practical value.

5.3. Evaluation and future directions of 4-on/8-off watchkeeping systems

The existing 4-on/8-off watchkeeping system has been the backbone of maritime operations for many years, providing a standardized approach to crew scheduling that ensures the continuous monitoring of vessel operations. This structure is widely adopted across various types of vessels, and has become the norm due to its simplicity, operational consistency, and ease of management (Balandong et al., 2019). The system typically assigns crew members to 4-h watch periods followed by 8 h of off-duty time. These watch periods may vary slightly, but the most common arrangement consists of alternating 4-h watch, such as 0000–0400 and 1200–1600, 0400–0800 and 1600–2000, 0800–1200 and 2000–2400. The enduring success and adoption of this watch system are grounded in its practicality and efficiency. By ensuring that a crew member is always on duty for 4 h at a time, and allowing for 8 h of rest, it helps balance operational demands with the need for crew presence at all times. Moreover, the predictable structure of the system allows for easy scheduling and clear expectations regarding crew availability. For decades, this arrangement has been deemed sufficient to mitigate the immediate risks associated with fatigue, particularly when crew members are vigilant and well-rested (van Leeuwen et al., 2021a). However, despite its long-standing use and apparent effectiveness, the 4-on/8-off system has significant limitations, particularly in relation to sleep recovery and crew well-being. A major disadvantage of this system is the insufficient duration of rest periods for effective sleep recovery. The 8-h off-duty period may appear adequate, but in practice, the actual time available for sleep is considerably less. Sleep is often split into two segments: a main core sleep period and a shorter nap. This division results in a total actual sleep time of approximately 7 h per 24-h cycle, which is less than ideal for preventing sleep deprivation, especially when officers are required to work during the early morning or late-night watch (Heikkilä, 2016).

Research indicates that the 4-on/8-off system fails to allow sufficient recovery from sleep deprivation, particularly in cases where the core sleep is interrupted (Heikkilä, 2016). When sleep is fragmented, as is the case with this schedule, it does not allow the body and mind the necessary restorative periods to fully recover. As a result, cognitive performance declines, alertness diminishes, and decision-making becomes impaired, particularly during critical tasks that demand heightened vigilance, such as navigation under adverse weather conditions or when operating in busy maritime traffic (Shi et al., 2024b). Additionally, the system's reliance on nap periods as a compensatory measure for insufficient sleep may not be effective in preventing fatigue, as the duration and quality of naps are typically inadequate to make up for the sleep debt incurred from interrupted or insufficient core sleep. Furthermore, the current system does not account for the variability in crew members' individual physiological needs and cognitive states. Each watchkeeper's ability to recover and perform effectively is influenced by factors such as circadian rhythms, physical health, and the cumulative fatigue experienced over multiple watch. The rigid structure of the 4-on/8-off system does not allow for adjustments based on these individual differences, which can lead to performance degradation, especially for officers working during the nocturnal or early diurnal hours. Circadian misalignment, when crew members are required to work opposite their natural sleep-wake cycles, significantly exacerbates fatigue and cognitive impairment (Fan and Yang, 2024). This misalignment is particularly problematic when officers are required to perform tasks that demand sustained attention and quick decision-making, where lapses in judgment can result in hazards.

Moreover, while the system does prevent fatigue build up by providing regular rest periods, it does not adequately address the issue of recovery during periods of excessive fatigue. In situations where officers experience extended wakefulness or face particularly demanding operational conditions, the system provides limited flexibility to extend rest periods or adjust schedules. This limitation restricts the crew member's ability to recover effectively from accumulated sleep deprivation, leaving them vulnerable to fatigue-related errors and reduced vigilance.

Moving forward, the integration of technology-assisted scheduling systems presents a promising avenue for improving the existing watchkeeping system. Real-time physiological data from IoT-enabled wearables and AI-driven analytics could enable more personalized and adaptive scheduling, tailoring watch periods based on individual sleep patterns, fatigue levels, and cognitive states. Such systems could continuously monitor crew members' physical and cognitive states, providing data-driven insights to optimize recovery times and crew performance. By adjusting schedules to accommodate both operational requirements and crew well-being, this approach could enhance safety and reduce fatigue-related errors in maritime operations. While implementing such systems would require substantial empirical testing and refinement, their potential to revolutionize crew management and significantly improve overall safety is considerable.

6. Conclusions, limitations and future directions

6.1. Conclusions

This study introduces an innovative integrated multidimensional analytical model, termed EWTM, which incorporates four distinct analytical methods: EMARM, WINGS, TAHDT and MICMAC. The application of the EWTM model reveals substantial variations in the crucial RIFs linked to maritime accidents across different watchkeeping periods. By integrating these analytical techniques, the EWTM model demonstrates its efficacy as a comprehensive and multidimensional tool for analysing accident characteristics and key RIFs during different watchkeeping periods. This study offers the maritime industry a robust theoretical foundation for developing accident prevention strategies tailored to specific watchkeeping periods. The model aims to enhance risk control and safety assurance through refined management practices, ultimately striving for optimal safety outcomes.

The results presented in this study underscore the necessity of implementing tailored risk management measures for each watchkeeping period, based on the specific RIFs encountered. Precise management of these RIFs during their respective watchkeeping periods is essential for systematically improving maritime safety and reducing the likelihood of accidents. Additionally, fostering a comprehensive understanding of these RIFs and enhancing the crew's ability to respond to them are vital for ensuring the long-term safe operation of ships.

6.2. Limitations and future directions

This study has innovatively explored the critical RIFs of maritime accidents across different watchkeeping periods, providing valuable insights for enhancing maritime safety. Nevertheless, certain limitations remain that should be addressed in future research. Firstly, although this study utilizes a substantial dataset of maritime accident investigation reports, the sample may exhibit bias and may not fully represent all possible accident scenarios. Future research should aim to expand the dataset's scope and diversity to enhance the generalizability and accuracy of the findings. Secondly, the identification of RIFs primarily depends on existing investigation reports and expert insights, which may not encompass all relevant factors affecting maritime accidents. Future studies should consider incorporating additional data sources, such as real-time ship operation and environmental monitoring data, to provide a more comprehensive assessment of potential RIFs. Finally, while this study proposes a prevention strategy based on watchkeeping period heterogeneity, practical implementation may encounter challenges. Future research should include field validation and feedback to refine the strategy's operability and effectiveness, ensuring its successful application in maritime management.

CRediT authorship contribution statement

Xinjian Wang: Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization. **Wenjie Cao:** Writing – original draft, Methodology, Conceptualization. **Tianyi Li:** Visualization, Methodology, Formal analysis. **Yinwei Feng:** Writing – review & editing, Validation, Methodology, Data curation. **Özkan Uğurlu:** Writing – review & editing, Validation, Formal analysis. **Jin Wang:** Writing – review & editing, Validation, Supervision, Investigation, Formal analysis.

Data availability

Data will be made available on request. The source code is publicly available at: https://github.com/FengYinLeo/difference-between-different-watchkeeping-periods.

Declaration of competing interest

The authors 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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Appendix A. The description of the maritime accident RIFs database

Table A
The description of the maritime accident RIFs database.

Level I	Level II	Variables	Value/definition
Human	Physical & Psychological state	HPS	poor, good
	Education background	HEB	poor, good
	Time at sea	HTS	<5 years, 5≤ time <10 years, ≥10 years
	Time in present rank	HTR	<1 year, 1 ≤ time <5 years, ≥5 years
	Communication problem	HC	yes, no
	Operational error	HO	yes, no, unknown
	Violation operation	HV	yes, no, unknown
Ship	Age	SA	0–10 years, 10–20 years, 20–30 years, ≥30 years
	Ship type	ST	Bulk carrier, Container ship, Oil tanker, Passenger ship (including cruise and ro-ro passenger ship), Chemical tanker, General cargo ship, Fishing vessel, Yacht and sailing vessel, Tug and port traffic boat, Others
	Gross tonnage	SG	<500 t, 500–3000 t, ≥3000t
	Engine power	SE	<750 KW, 750–3000 KW, ≥3000 KW
	Flag state	SF	Flag of convenience, Not flag of convenience
	Ship's certificates	SSC	complete and valid, incomplete or invalid
	Ship manning	SM	adequate, inadequate
	Seafarers' certificates	SC	complete and valid, incomplete or invalid
	Seaworthiness	SS	yes, no
	PSC/FSC inspection	SPF	unsure, sure
Environment	Location	EL	Inland waters, Port, Coastal waters, Open Sea
	Visibility	EV	very poor - Vis <0.5 nm, Poor - 0.5 ≤ Vis <2 nm, Moderate - 2 ≤Vis <5 nm, Good and very good - Vis ≥5 nm
	Wind force	EW	0-5, 6–7, 8–9, 10-12
	Sea state	WS	0-3, 4–5, 6–7, 8-9
	Current speed	EC	<2kn, 2-4kn, ≥4kn
	Traffic density	ET	low, high
	Fairway width/ship length	EF	w/l < 1, 1 ≤ w/l < 2, w/l ≥ 2
	Depth-draft ratio (h/d)	ED	h/d < 1.2, 1.2 ≤ h/d < 1.5, 1.5 ≤ h/d < 3, h/d ≥ 3
Management	Regulation	MR	inadequate, adequate

(continued on next page)

Table A (*continued*)

Level I	Level II	Variables	Value/definition
	Supervision	MS	inadequate, adequate
	Violation in supervision	MV	yes, no
	Safety management system	MSS	defective, non-defective
	Safety management	MSM	inadequate, adequate
	Rectification of problems	MRP	unresponsive, responsive
	Company safety culture	MC	poor, good
	Training	MT	inadequate, adequate
	Drill	MD	off schedule, stick to the schedule

Appendix B. The results of hierarchy analysis

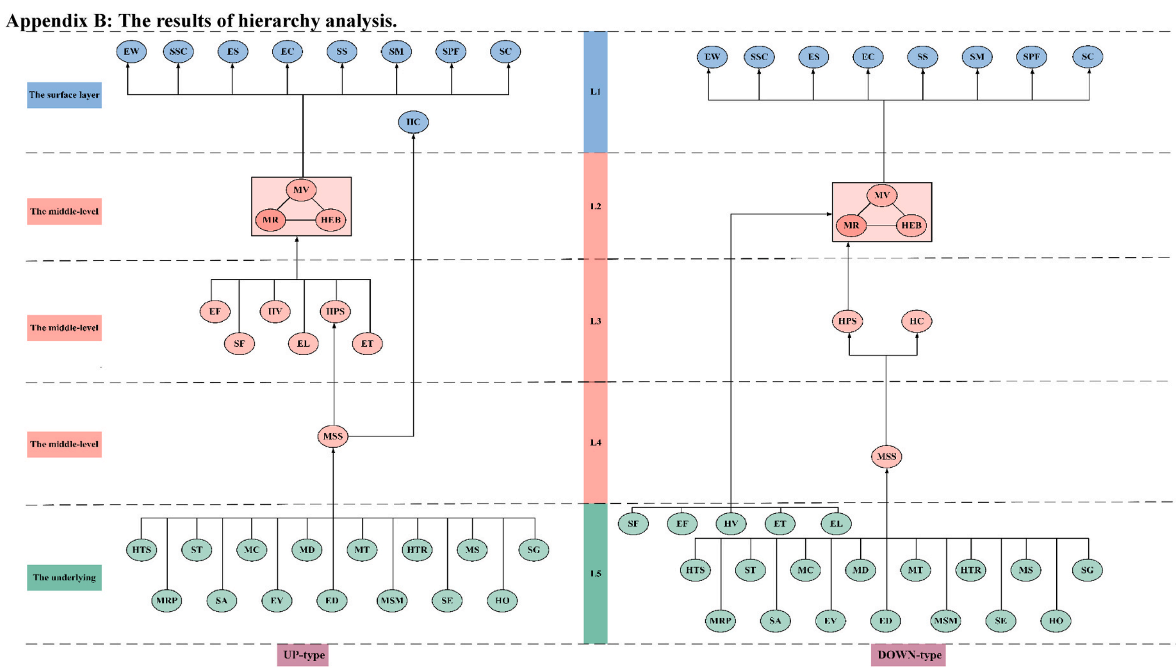

Fig. B.1. The causal diagram of RIFs (Second Officer).

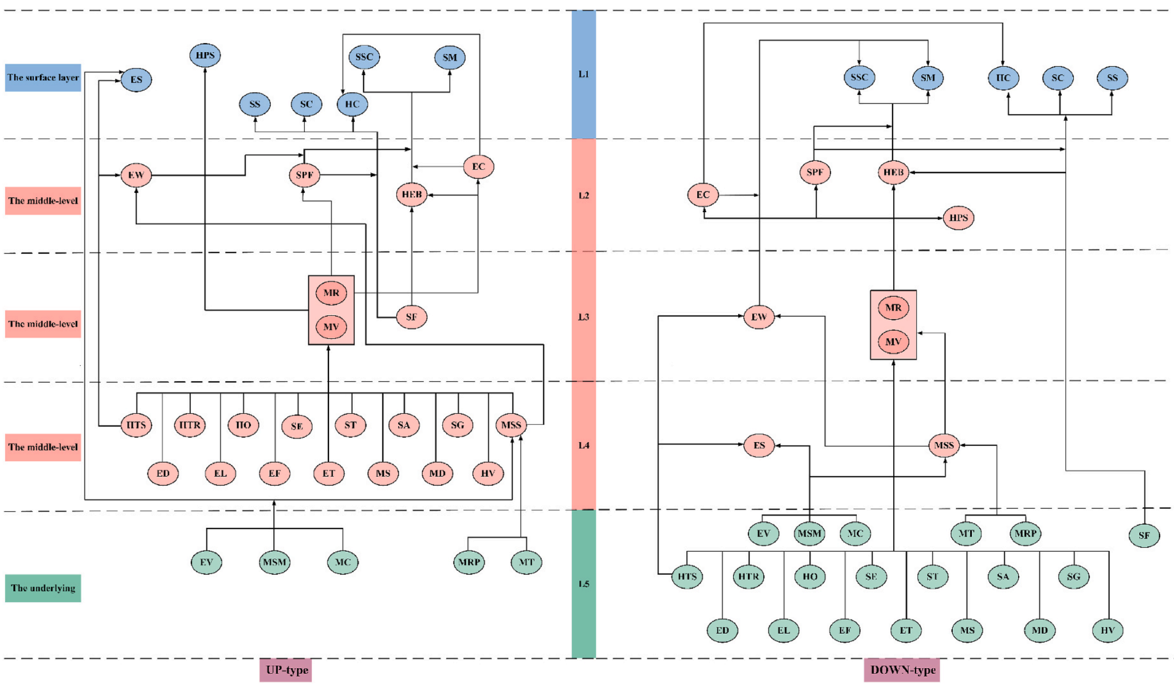

Fig. B.2. The causal diagram of RIFs (Chief Officer).

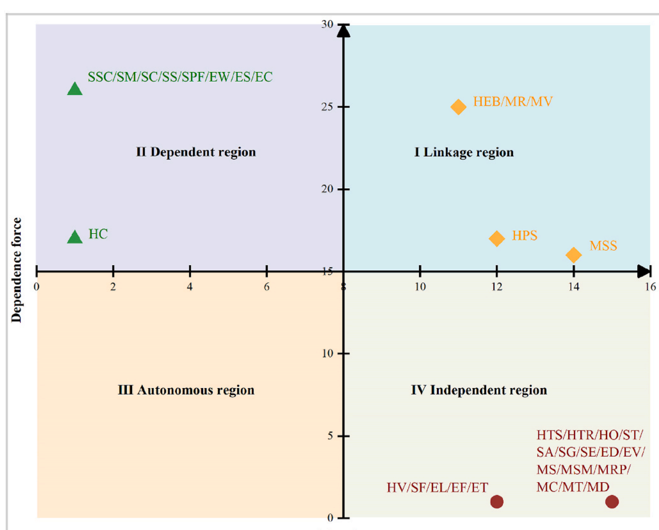

Fig. B.3. Classification chart of RIFs (Second Officer).

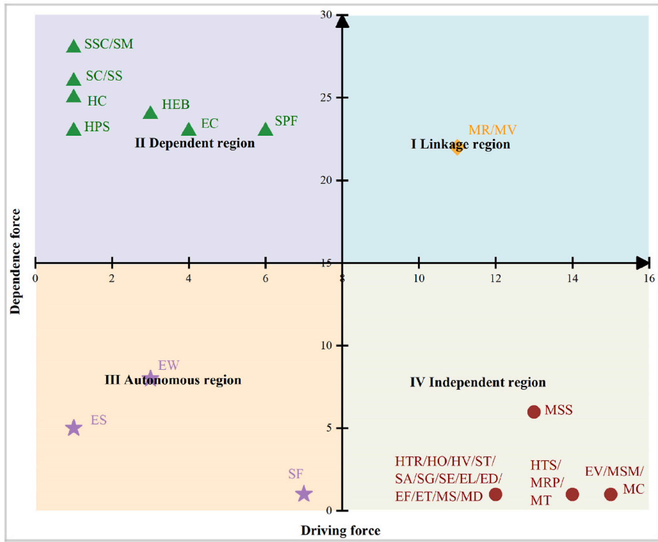

Fig. B.4. Classification chart of RIFs (Chief Officer).

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