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Analysis Of Influential Factors Of Maritime Accidents In Different Waters Based On Combined-AR And DEMATEL

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Abstract

Although maritime accidents have occurred from time to time, the risk of accidents varies among different waters. This study aims to explore the causation mechanism of maritime accidents in different waters by identifying the key risk influential factors (RIFs) of maritime accidents in different waters and analyzing the intricate relationships among them through the Combined-Association rules and Decision-Making Trial and Evaluation Laboratory (DEMATEL) model. Firstly, 34 RIFs in 5 categories are identified based on the literature review and analysis of marine accident investigation report. Secondly, the maritime accident datasets are classified into 4 categories according to the locations of the accidents which include inland waters, ports, coastal waters and open waters. Thirdly, the relationships among RIFs are explored by combined-AR and displayed by a direct influence matrix, and the matrix is then normalized by DEMATEL and a comprehensive influence matrix is obtained. Finally, the influence degree, affected degree, centrality degree, reason degree, and weights of each RIF are calculated to determine the extent to which it holds a causal or consequential position in the complex system. The results indicate that among the 34 RIFs, lack of experience, operational errors in human-related factors, and gross tonnage in ship-related factors have a significant direct impact on maritime accidents in all water areas. However, the key RIFs for maritime accidents in different waters vary a lot. Ship manning has the highest impact on accidents in inland waters and ports, while physical and psychological state and education background are key RIFs for accidents in coastal waters and open waters respectively. Based on the RIFs identified in this study, the evolutionary mechanism of maritime accidents in different waters and the relationships among these RIFs are analyzed, and key RIFs for maritime accidents in different waters are obtained, which is expected to be beneficial for the improvement of maritime safety in different waters.

Keywords: maritime safety, maritime accidents, Combined-AR, DEMATEL, risk analysis

1. Introduction

In recent years, concerns persist over the frequent occurrence of maritime accidents with the continuous development of the shipping industry and the expanding global trade (Ugurlu and Cicek, 2022). Therefore, in-depth research and analysis of maritime accidents are crucial for seeking effective preventive and responsive measures to maintain maritime safety (Ahmed et al., 2023). Although various measures have been adopted in the maritime transportation sector to enhance safety, accidents continue to occur frequently, and there has been no significant improvement in the safety situation. The rapid growth of the global shipping industry at the present stage has led to a swift increase in the scale of operational vessels. This has resulted in a growing significance of navigational order issues, coupled with an increasingly complex array of waterway types globally. The complexity and diversity of maritime accidents continue to present a challenging problem in identifying and preventing the root causes (Fan et al., 2020; Weng et al., 2020).

Maritime accidents are influenced by a multitude of factors, and these factors are interconnected. Currently, scholars in the industry employ various models to quantitatively study the changing trends of maritime accidents. Özdemir and Güneroglu (2015) employed the Analytic Network Process (ANP) method to comprehensively assess the mutual influence among maritime accident factors, thereby determining the significance of human factors. Additionally, Awal and Hasegawa (2017) utilized Logic Programming Technology (LPT) to analyze and comprehend the causation of accidents. Moreover, Puisa et al. (2018) employed the System-Theoretic Accident Model and Processes (STAMP) along with its causal analysis method, CAST, to analyze the weakest links in maritime safety control, providing an analysis of the causal factors in accident reports. Furthermore, Chin and Debnath (2009) utilized an ordered probit regression model to predict ship collision risks and subsequently calibrates the regression model. In summary, existing research, while having practical implications for safeguarding maritime traffic and enhancing the level of maritime traffic safety management, its limitations lie in the fact that existing research methods have not thoroughly investigated the interrelationships among causal factors.

Two methods, namely Combined-Association rules and Decision-Making Trial and Evaluation Laboratory (DEMATEL), are applied comprehensively to analyze various maritime accidents in different waters and accurately evaluate the relationship between RIFs. Firstly, 34 RIFs in 5 categories, that is human, ship, management, environment and basic accident information, are identified based on the literature review and accident investigation report analysis. Secondly, the maritime accident datasets are classified into 4 categories according to the locations of the accidents which include inland waters, ports, coastal waters and open waters. Thirdly, the relationships among RIFs are explored by combined-AR and displayed by a direct influence matrix, and the matrix is then normalized by DEMATEL and a comprehensive influence matrix is obtained. Finally, the influence degree, affected degree, centrality degree, reason degree, and weights of each RIF are calculated to determine the extent to which it holds a causal or consequential position in the complex system. The research findings can provide support for relevant authorities in formulating policies for the prevention of maritime accidents.

2. Materials and method

2.1. Data set

In this study, maritime accident investigation reports published by seven maritime investigation agencies from 2000 to 2019, namely China Maritime Safety (China MSA), Federal Bureau of Maritime Casualty Investigation (BSU), National Transportation Safety Board (NTSB), Japan Transportation Safety Board (JTSB), Australian Transport Safety Board (ATSB), Canadian Transportation Safety Board (TSB), and Marine Accident Investigation Branch (MAIB), were collected as the primary data source.

Before analyzing these investigation reports, it was observed that these accident investigation reports vary in degree of detail, and even some of the data is inaccurate and/or incomplete. Therefore, adhering to the principles of data authenticity and completeness, accident reports with incomplete data were excluded, and a dataset of 1294 accident reports was obtained. As this study focuses on the causation analysis of maritime accidents in different water areas, all accident investigation reports were further categorized based on the types of water areas where the accidents occurred. This process resulted in a final breakdown of maritime accident data, with 154 accidents in inland waters, 523 in ports, 503 in coastal areas, and 114 in open waters. Based on the identification of RIFs through text analysis and expert judgment with reference to relevant literatures (Wang et al., 2021; Wang et al., 2022), this study established a database of the RIFs of maritime accidents so as to meet the data requirements for association rule mining (Toivonen, 1996). The database includes 34 RIFs across five dimensions: human, vessel, management, environment, and basic accident information, as shown in Table 1.

Table 1. RIFs of maritime accidents.

Category	Second category	Codes	RIFs
Accident	Accident type and severity	AT	Accident type
		S	Accident severity
	Date and time	M	Month
		T	Time
Human	Human factors	PP	Physical and psychological state
		E	Education background
		TS	Time at sea
		TR	Time in present rank
		C	Communication problem
		OE	Operational error
		VO	Violation operation
Ship	Ship particulars	ST	Ship type
		SA	Age
		G	Gross tonnage
		EP	Engine power
		F	Flag state
	Voyage data	SM	Ship manning
Environment	External environment	V	Visibility
		WF	Wind force
		SS	Sea state
		CS	Current speed
	Navigational/geographical condition	TD	Traffic density
		WL	Fairway width/Ship length
		DD	Depth-draft ratio (h/d)
Management	Administration	R	Regulation
		SUP	Supervision
		VS	Violation in supervision
		PF	PSC/FSC
	Company factors	SAS	Safety system
		SAM	Safety management
		RP	Rectification of problems
		CC	Company safety culture
		TRA	Training
		D	Drill

2.2. Proposed methodological approach

2.2.1 Combined-AR

As one of the core of data mining technology, association rule mining can discover the potentially valuable relationships like co-occurrence, causation and correlation among item sets from complex chaotic datasets (Kotsiantis and Kanellopoulos, 2006). The associations unearthed through association rule mining can serve as substitutes for expert ratings, thereby eliminating the influence of subjective factors (Zaki and Ogihara, 2007). The formulae for the association rules are shown in equations (1) to (3).

$$Support(A) = \frac{N_A}{N} \tag{1}$$

$$Confidence(A \Rightarrow B) = \frac{Support(AB)}{Support(B)} \tag{2}$$

$$Lift(A \Rightarrow B) = \frac{Confidence(A \Rightarrow B)}{Support(B)} \tag{3}$$

In these equations, $Support(A)$ represents the support of item set A; N_A denotes the frequency of item set A occurs in the data; and N represents the total number of data instances; $Confidence(A \Rightarrow B)$ signifies the confidence of item set A leading to item set B, with item set A as the antecedent and item set B as the consequent; $Lift(A \Rightarrow B)$ denotes the lift of item set A to item set B, indicating the extent to which the probability of B occurring is elevated when A occurs.

Support indicates the frequency of occurrence of an item set. Confidence represents the probability of the consequent occurring when the antecedent is present. Lift reflects the enhancing effect of the antecedent's occurrence on the probability of the consequent occurring. If the lift is greater than 1, it signifies that the presence of the antecedent promotes the occurrence of the consequent. Many researchers consider association rules with a lift greater than 1 as effective(Agrawal and Srikant, 1998). Confidence indicates the degree of influence that the antecedent has on the consequent; a higher confidence value implies a stronger impact. Therefore, in this study, association rules with a lift greater than 1 are selected as effective, and the confidence value is used to replace expert ratings.

When mining the data with various states such as ship type and ship age, the traditional association rule mining techniques can only analyze the different states of each factor, but can not obtain the overall association relationships with other factors (Srikant and Agrawal, 1997). To address this limitation, this study introduces the Combined-AR algorithm, which is built upon traditional association rule mining. The formula and pseudocode of the Combined-AR are respectively presented in (4) and Table 2.

$$Confidence(A \Rightarrow B) = \sum_i \sum_j Confidence(a_i \Rightarrow b_j) \times \frac{Support(a_i \Rightarrow b_j)}{\sum_i \sum_j Support(a_i \Rightarrow b_j)} \tag{4}$$

where, a_i denotes the different states of factor A, b_j represents the distinct states of factor B, and $Support(a_i \Rightarrow b_j)$ signifies the support from the various states of factor A to the different states of factor B.

Table 2. The pseudocode of Combined-AR algorithm.

Algorithm 1: Combined-Association Rule algorithm
Input: Dataset, **DS**; Minimum support threshold, **min_sup**
Output: Combined_AR
Begin
Calling Association Rule algorithm (Apriori, FP-Growth, etc.)
Return association rules that satisfy **min_sup** and **lift > 1, AR**
Generate two matrices **CM** and **SM** with $Conviction(a_i \Rightarrow b_i)$ and $Support(a_i \Rightarrow b_j)$ as elements, respectively, based on the **AR**
Use (5) to perform scaling nodes operations are performed on CM and SM based on factors states to form new matrices, **NCM**
Change the diagonal of **NCM** to all Zeros, **CARM**
Transforming **CARM** matrix into association rule format
Return Combined_AR
End

2.2.2. DEMATEL

The occurrence of maritime accidents is not purely incidental but rather the result of the combined effects of various factors (Cao et al., 2023). The interaction among RIFs in maritime accidents constitutes a complex system. Analyzing the dependencies and causal relationships among the core elements of the complex system can be effectively achieved through the DEMATEL method (Si et al., 2018). The traditional DEMATEL approach involves an expert team to assist in determining the degree of influence between factors, facilitating a deeper understanding of the analyzed problem. However, the validity of expert opinions and the setting of weights are crucial considerations. To eliminate subjective factors, this study employs a purely data-driven approach to construct the DEMATEL model (Feldmann et al., 2022).

The specific process of this method is outlined as follows:

Step 1: Construct the Direct Impact Matrix based on Combined-AR, as presented in equations (5) to (7).

$$G = \begin{array}{c} \\ Fa_1 \\ Fa_2 \\ \vdots \\ Fa_e \end{array} \begin{array}{c} \begin{array}{cccc} Fa_1 & Fa_2 & \cdots & Fa_e \end{array} \\ \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1e} \\ g_{21} & g_{22} & \cdots & g_{2e} \\ \vdots & \vdots & & \vdots \\ g_{e1} & g_{e2} & \cdots & g_{ee} \end{bmatrix} \end{array} \tag{5}$$

$$g_{AB} = e_{AB} \times Conviction(A \Rightarrow B) \tag{6}$$

$$e_{AB} = \begin{cases} 1, \text{ when a combined} - \text{association rule exists from A to B} \\ 0, \text{ else} \end{cases} \tag{7}$$

where, G stands for the Direct Impact Matrix; Fa_i represents a particular RIF under analysis in this study; g_{AB} denotes the impact level of factor A on factor B, e_{AB} indicates the presence of a strong correlation between factor A and factor B, with 1 denoting a strong correlation and 0 denoting otherwise.

Step 2: Normalize the Direct Impact Matrix and obtain the Normalized Impact Matrix, as shown in equations (8) to (11).

$$Para = \frac{1}{(\max(a_1, a_2, \cdots, a_p)^2 + \max(b_1, b_2, \cdots, b_p)^2)^{1/2}} \tag{8}$$

$$a_i = \sum_j g_{ij} \tag{9}$$

$$b_i = \sum_j g_{ji} \tag{10}$$

$$NorG = Para \times G \tag{11}$$

where, $Para$ is the normalization parameter; a_i denotes the summation directly influencing the i^{th} row of the matrix, b_i represents the summation directly influencing the i^{th} column of the matrix; $NorG$ signifies the normalized impact matrix.

Step 3: Construct the comprehensive impact matrix using the theory of transitivity of influence, as shown in (12):

$$T = \sum_{k=1}^{\infty} NorG^k = NorG \cdot (E - NorG)^{-1} = (t_{ij})_{e \times e} \tag{12}$$

where, T stands for the comprehensive impact matrix; $\cdot$ is indicative of the matrix product; E represents the identity matrix; and t_{ij} signifies the overall impact of factor i on factor j within the comprehensive impact matrix. It is crucial to emphasize that (13) holds under the precondition that all elements in the matrix fall within the [0, 1] range, and the diagonal elements of the matrix are uniformly set to 0, implying that factors do not exert influence on themselves.

Step 4: Calculate the influence degree, affected degree, centrality degree, reason degree and weight of each factor according to the comprehensive impact matrix, as shown in equations (13) to (17).

$$I_i = \sum_j t_{ij} \tag{13}$$

$$BI_i = \sum_j t_{ji} \tag{14}$$

$$CE_i = I_i + BI_i \tag{15}$$

$$RE_i = I_i - BI_i \tag{16}$$

$$Weight_i = \frac{(CE_i^2 + RE_i^2)^{1/2}}{\sum_i (CE_i^2 + RE_i^2)^{1/2}} \tag{17}$$

where, I_i stands for the influence degree of factor i; BI_i represents the influenced degree of factor i; CE_i signifies the centrality of factor i; RE_i indicates the causality of factor i; and $Weight_i$ represents the weight of factor i.

3. Analysis and discussion

3.1. Analysis of Combined-AR results

To explore the potential relationships among various RIFs, 2082 original association rules and 824 joint association rules were mined in this study by the Apriori algorithm (Zhou et al., 2019). The confidence level serves as an indicator of the association rules' strength, the higher the confidence ranking is, the stronger the interaction between adjacent RIFs in the complex network is. The top 10 association rules with the highest confidence levels for maritime accident causation in the four types of water areas are shown in Table 3.

It can be seen from Table 3 that the top-ranking association rules in any water areas are almost related to human factors and management factors. In inland waters, the interaction between operational errors, port state control inspections and other ship-related factors are strongest in the network. In ports, coastal waters and open waters, there is strong associations between inadequate crew communication and inadequate crew education and training, as well as lack of routine training and lack of onboard experience.

On the whole, the RIF C (Communication problem) is most likely to occur in maritime accidents. However, there are some differences in other factors closely associated with factor C for accidents in different water areas. In port waters, the factors with strongest interaction with factor C are ship type and crew's physical and psychological states. In coastal waters, the factors RIF C most are PSC/FSC inspections and current speed. In open waters, the factors with the strongest interaction with factor C are crew education background and ship manning. Therefore, these factors should be distinctly emphasized and judiciously controlled in different water areas.

Table 3 Top 10 Combined-AR ranked by confidence values.

Areas	No.	Antecedent	Consequent	Confidence	No.	Antecedent	Consequent	Confidence
Inland waters	1	TS	PF	0.98634	6	OE	SAM	0.96154
	2	C	PP	0.98276	7	OE	D	0.96047
	3	OE	F	0.97201	8	DD	PP	0.96000
	4	OE	PF	0.97196	9	SS	PF	0.95833
	5	OE	R	0.96321	10	VS	TD	0.95826
Ports	1	ST	C	0.98335	6	AT	C	0.97631
	2	PP	C	0.98268	7	DD	C	0.97464
	3	E	C	0.97949	8	SAS	C	0.97453
	4	TS	C	0.97828	9	F	C	0.97345
	5	TR	C	0.97702	10	CC	C	0.97322
Coastal areas	1	PF	C	0.96444	6	TS	C	0.96050
	2	CS	C	0.96335	7	PP	C	0.95930
	3	SM	C	0.96214	8	TR	C	0.95683
	4	R	C	0.96184	9	VS	C	0.95658
	5	E	C	0.96128	10	SAS	C	0.95430
Open waters	1	E	C	0.98357	6	TS	C	0.98087
	2	SM	C	0.98210	7	SS	C	0.98083
	3	TR	C	0.98188	8	PP	C	0.98081
	4	CS	C	0.98157	9	WF	C	0.98035
	5	R	C	0.98156	10	AT	C	0.98009

3.2. Causality analysis of RIFs based on DEMATEL

In this study, the Direct Impact Matrix G for each water area was constructed according to, equations (5) to (7). The Direct Impact Matrices were then normalized using equations (8) to (11), the normalized matrices $NorG$ where all elements fall within the [0, 1] range were obtained. The Comprehensive Impact Matrix T was then obtained by (12). Finally, the influence degree I, affected degree BI, centrality degree CE, causality degree RE, as well as weights $Weight$ of the RIFs of maritime accidents in each water area were calculated using equations (13) to (17). A causal distribution graph of RIFs was illustrated by plotting the values of centrality and causality in Table 4, as shown in Figure 1.

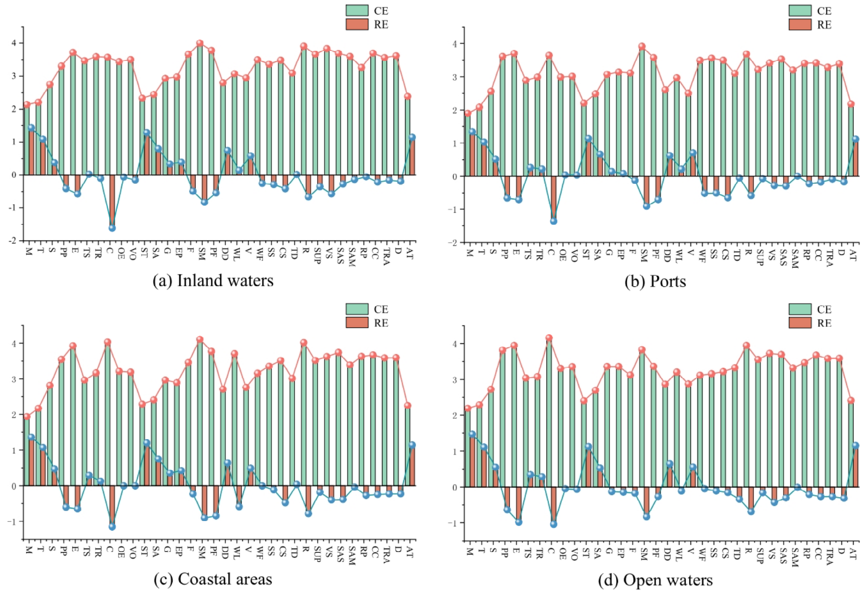

Fig. 1. The Weight Distribution Graph of Maritime Accident Impact Factors.

The centrality degree (CE) value serves as an indicator of a factor's influence on the overall complex system, and the greater the CE value, the more significant the influence of the factor on maritime accidents. As illustrated in Figure 2, the top 5 factors that have the most significant impact on maritime accidents in inland waters are SM (Ship Manning), R (Regulation), VS (Violation in Supervision), PF (PSC/FSC), and E (Education Background). Their centrality degrees are 3.9996, 3.9095, 3.8363, 3.7820, and 3.7226, respectively. In port waters, the leading factors influencing maritime accidents are SM (Ship Manning), E (Education Background), R (Regulation), C (Communication Problem), and PP (Physical and Psychological State), with centrality degrees of 3.9147, 3.7013, 3.6852, 3.6458, and 3.6116. For maritime accidents in coastal waters, the five most RIFs are SM (Ship Manning), C (Communication Problem), R (Regulation), E (Education Background), and PF (PSC/FSC), with centrality degrees of 4.1074, 4.0318, 4.0161, 3.9248, and 3.7669, respectively. In open waters, the factors with the most substantial impact on maritime accidents are C (Communication Problem), R (Regulation), E (Education Background), SM (Ship Manning), and PP (Physical and Psychological State), with centrality degrees of 4.1600, 3.9457, 3.9441, 3.8278, and 3.8125, respectively. These RIFs are closely related to other factors in maritime accidents, so it is necessary to carry out more detailed risk management approaches for vessels navigating in different water areas.

The causality degree (RE) value reflects the degree to which a factor occupies a causal position within a complex system. If RE > 0, it indicates that the factor is a causative influence on other factors. Conversely, if RE < 0, the factor is influenced by other factors and serves as a resultant factor. It can be seen from Table 4 and Figure 1 that, the causality degrees (RE) of RIFs M (Month), ST (Ship Type), AT (Accident Type) and T (Time) all exceed 1 for maritime accidents in three distinct water areas—inland waters, ports, and coastal waters, which indicates that these factors have the most significant influence on other elements. Meanwhile, the factors with the smallest causality degrees are C (Communication Problem) and SM (Ship Manning). The causality values of both factors are less than -1, indicating their susceptibility to the influence of other elements within the complex system. Similarly, in open waters, the leading four factors with the highest causality degrees are M (Month), AT (Accident Type), ST (Ship Type), and T (Time), underscoring their substantial impact on other elements. The factors with the smallest causality degrees are C (Communication Problem) and E (Education Background), revealing their vulnerability to the influence of other factors.

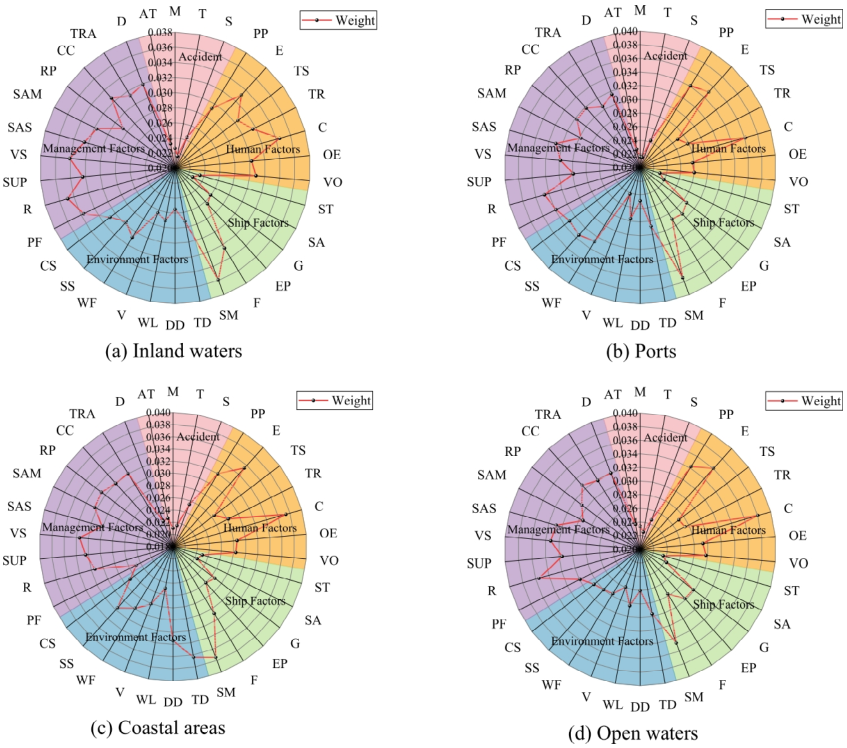

Fig. 2. The Weight Distribution Graph of Maritime Accident Impact Factors.

A comprehensive analysis of centrality degree (CE) and causality degree (RE) brings to light distinctive features within the RIFs of maritime accidents across various maritime areas. It is particularly noteworthy that the factor C (Communication Problem) has the highest centrality degree (CE) and the smallest causality degree (RE) in maritime accidents in inland waters. Similarly, the factor SM in port waters, factor PF in coastal waters, and factor E in open waters have the same characteristics. This suggests that these factors are significantly influenced by other factors, but have a relatively minor impact on other factors, highlighting their close relationship with other factors in the complex system and their direct influence on maritime accidents. Relatively speaking, the centrality and causality degrees of factors M (Month), ST (Ship Type) and AT (Accident Type) are relatively large, indicating that these factors indirectly affect maritime accidents by influencing other factors.

In the complex system governing the evolution of maritime accidents, Figure 2 visually illustrates the weight distribution of RIFs based on the Weight values in Table 4. Notably, in the complex system, the top five weight ranking for RIFs of maritime accidents in inland waters are SM (Ship Manning), R (Regulation), C (Communication Problem), VS (Violation in Supervision), and PF (PSC/FSC). In coastal waters, these factors are SM (Ship Manning), C (Communication Problem), E (Education background), R (Regulation), and PP (Physical and psychological state); for port waters, SM (Ship Manning), C (Communication Problem), R (Regulation), E (Education background), and PF (PSC/FSC); and in open waters, the factors are C (Communication Problem), E (Education background), R (Regulation), SM (Ship Manning), and PP (Physical and psychological state). The weight takes into account the attributes of centrality and causality, but downplays the influence of resultant and causative factors.

Through a comprehensive analysis of centrality, causality and weight of the RIFs of maritime accidents in four types of water areas, it is found that in any water area, ship manning, communication, and regulations are the most RIFs in maritime accidents. In addition, there are differences in the key RIFs for different water areas: in inland waters, Violation in Supervision is notably important; in port waters, the key RIFs include port-state inspections and flag-state inspections; whereas in coastal waters and open waters, physical and psychological state and education background surface as fundamental RIFs.

4. Conclusion

In this study, an integrated approach that combines Combined-Association rules and the DEMATEL model was proposed to analyze the key RIFs and their intricate relationships in maritime accidents. The results reveal that the degrees of direct impact exerted by human and vessel factors vary on maritime accidents in different waters. Insufficient experience and operational errors are the most important human factors that affect the maritime accidents in any water areas, while the gross tonnage of the ship plays a pivotal and direct role among ship-related factors. In addition, there are differences in the key RIFs in different waters. Notably, in inland waterways and ports, crew-related factors bear greater significance, while in coastal and open waters, psychological state and educational background stand out as fundamental factors.

Through a comprehensive analysis of the interrelationships among factors influencing maritime accidents, this study successfully elucidates the evolutionary mechanisms of these factors, providing a profound understanding of their dynamic developmental processes. Specific cause-and-effect relationships of maritime accident RIFs are delineated, offering crucial theoretical support for a deeper comprehension and intervention into maritime accidents. The research opens new avenues for enhancing vessel traffic safety in different waterways and provides theoretical guidance for formulating more effective safety management strategies. In practical terms, it offers valuable insights for effectively reducing the risk of maritime accidents and substantively contributes to accident avoidance.

This study, however, has certain limitations and shortcomings, which need further attention in future research: The analysis of maritime accident RIFs in this study is limited to four types of sea areas with a higher occurrence of accidents. The classification of water areas is relatively general, and future research could benefit from a more refined analysis of maritime accident RIFs for different types of water areas. The study primarily focuses on analyzing the differences in RIFs for maritime accidents occurring in different sea areas, without delving into the coupling effects between different states of the same factor. It is recommended that future research consider exploring such interactions to advance maritime safety and sustainable shipping development.

Appendix

Acronym	Full name	Acronym	Full name
DEMATEL	Decision-Making Trial and Evaluation Laboratory	T	Comprehensive Impact Matrix
Combined-AR	Combined Association Rules	I	Influence degree
RIF	Risk influential factors	BI	Affected degree
STAMP	Systems-Theoretic Accident Modeland Process	CE	centrality degree
CAST	Causal Analysis based on STAMP	RE	causality degree

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