

Article

An Integrated Framework of Association Rules and Social Network Analysis for Exploring Co-Occurrence Patterns of Waterborne Accident Causes

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Abstract

Accident cause analysis is widely valued by the International Maritime Organization (IMO) and many maritime authorities to prevent waterborne transportation accidents. In this study, 886 waterborne transportation accident investigation reports from China MSA are collected. Contributing factor analysis sections are extracted and imported into NVIVO for directed content coding, which combines the HFACS framework and grounded theory coding. In total, all contributing factors are identified, conceptualized, and categorized into 76 sub-categories across five dimensions. Based on these, association rule analysis is conducted separately for seven accident types to mine corresponding strong association rules. Meanwhile, an undirected co-occurrence social network is constructed with all accident samples and analyzed from three dimensions: connection strength, criticality, and activeness. Multi-dimensional network structure analysis shows that external influence accident causes do not rank among the top nodes across all indicators. Within the scope of this study, the contributing factor co-occurrence network presents a closed-like structural feature dominated by internal factors. “Failure to identify risks timely and take effective measures” and “Incompetent crew” are identified as two core nodes with outstanding comprehensive performance across multiple indicators. In addition, nodes with prominent local co-occurrence aggregation characteristics are also identified through clustering coefficient analysis.

Keywords: accident causes; waterborne transportation; HFACS; association rules; social network



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1. Introduction

The role of waterborne transportation in driving economic growth has become increasingly significant. For instance, as of 2023, 95% of China’s trade volume is delivered via waterborne transportation [1]. However, the safety level of waterborne transportation is always concerned by the public and administrative authorities because waterborne transportation accidents seem to be inevitable. Although the Ministry of Transport in China has implemented numerous policies to ensure the safety of waterborne transportation, statistics from the China Maritime Safety Administration (MSA) show that 321 waterborne

transportation accidents occurred in Chinese waters during 2021–2023. While this figure represents a 29% decrease compared to 2018–2020, the number of accidents has not yet reached the desired level. Waterborne transportation accidents often lead to significant property losses, casualties, and environmental damage, which to some extent hinder the stable development of the shipping industry. For instance, in the Qiongzhou Strait collision between the “Jiahe 128” and “Guichin Yu 22668” vessels, not only did the accident result in property damage and casualties, but it also caused a diesel spill, severely polluting the surrounding waters [2]. Obviously, investigating the accident causes and taking countermeasures are widely regarded as an effective way to prevent similar accidents, which is also valued by the International Maritime Organization (IMO). For this purpose, the mandatory rule of the Code of the International Standards and Recommended Practices for a Safety Investigation into a Marine Casualty or Marine Incident prepared by the IMO has been in force since 1 January 2010. Since then, the waterborne transportation accident investigation reports have been made public, and these accident investigation reports are widely accepted as an important medium to identify accident causes and prevent similar accidents. Motivated by further mining the great potential value of the public waterborne transportation accident investigation reports, this study tries to quantitatively assess various accident causes by means of association rule analysis and social network analysis. The salient features of this study are represented as follows.

- (1) A total of 886 waterborne transportation accident investigation reports issued by China MSA (2013–2023), covering seven accident types, are collected to construct the database. The data are reliable and informative for understanding the overall safety risks of waterborne transportation in China.
- (2) A hybrid deductive–inductive coding approach integrating grounded theory and the HFACS framework is adopted to extract and classify accident causes. Unlike text mining methods that primarily identify surface-level keywords and suffer from limited interpretability, this hybrid approach combines bottom-up conceptualization from raw report texts with top-down theoretical classification, enabling more systematic and interpretable identification of causation factors.
- (3) An integrated analytical framework is developed to characterize interactions among accident causes. It combines association rule analysis with undirected weighted co-occurrence network analysis based on social network analysis. Rooted in the co-occurrence relations documented in original investigation reports, both methods avoid imposing forced causal hierarchies and remain faithful to how accident causes are actually presented in investigation texts.

The remainder of this paper is organized as follows: Section 2 presents the literature review, and Section 3 outlines the proposed methodology and guiding principles. Data collection and description are provided in Section 4, while Section 5 covers the analysis and discussion of the causes of accidents. The paper concludes in Section 6.

2. Literature Review

Multi-tiered institutional systems and standardized paradigms for maritime accident investigation and causation analysis have been developed across international, regional and national levels to support evidence-based safety prevention. The IMO has issued the mandatory Casualty Investigation Code and operates the GISIS database with a unified cause classification scheme for member states. At the European Union (EU) regional level, the European Maritime Safety Agency (EMSA) promotes systemic investigation methodologies including Casualty Analysis Methodology for Maritime Operations (CASMET), is technically compatible with HFACS-derived frameworks such as HFACS-MA for national use, and has developed the unified European Marine Casualty Information Platform (EM-

CIP) taxonomy for harmonized cause coding across EU member states [3]. At the national level, representative independent investigation bodies such as the U.S. National Transportation Safety Board (NTSB) and the UK Marine Accident Investigation Branch (MAIB) follow a systemic, no-blame investigative philosophy: their work centers on identifying underlying accident causes and issuing safety recommendations, and does not involve assigning fault or determining liability [4,5].

Collectively, these institutional frameworks reflect a global consensus on systemic accident investigation that extends beyond immediate failures to consider interactive associations of contributing factors. In line with this paradigm, numerous maritime safety studies have been conducted based on official investigation reports from various national and international authorities. Table 1 provides an overview of the relevant literature.

Table 1. Studies on the accident cause analysis based on a collection of waterborne accidents.

Sources	Data/Accident Scenario	Methodology
Qiao et al. [6]	394 ship-foundering accidents in China	Human factor analysis and classification system (HFACS), fuzzy aggregation
Ma et al. [7]	520 accidents occurred in Arctic waters during 2011–2020	Bayesian network (BN), HFACS, association rule analysis
Maceiras et al. [8]	276 maritime accidents in Spain	Random forest, clustering and neural networks
Ma et al. [9]	189 maritime accidents in Australia during 2000–2022	Data-driven BN
Ma et al. [10]	980 maritime accidents in the Liaoning Sea area during 2000–2023	BN
Munim et al. [11]	Historical data of maritime accidents in Norway during 1981–2020	Automated machine learning
Li et al. [12]	362 global maritime accidents during 2017–2021	Multinomial logit model with adaptive sparse group lasso penalty
Ma et al. [13]	104 ship grounding accidents during 2011–2022	HFACS, grounded theory, Chi-square test and Odds Ratio, complex network
Ma et al. [14]	383 maritime accidents during 2012–2020	HFACS, grounded theory, BN, association rule analysis
Huang et al. [15]	4933 accidents in the Mediterranean Sea and Black Sea during 2006–2020	Weighted association rule mining
Zhou et al. [16]	5537 global maritime accidents during 2001–2020	Integration of spatial density analysis and XGBoost
Deng et al. [17]	123 maritime accidents along China's coast during 2000–2020	Complex network, PageRank algorithm
Mok et al. [18]	2967 maritime accidents in Korea during 1989–2020	Multilateral comparative analysis
Sui et al. [19]	3285 maritime accidents in the Yangtze River during 2011–2020	VG algorithm, complex network
Yang et al. [20]	549 maritime accidents in the Fujian sea area during 2007–2020	Random forest, AdaBoost, gradient boosting decision tree, stacking
Li et al. [21]	402 global maritime accidents during 2017–2021	BN
Lan et al. [22]	1554 global maritime accidents during 2010–2020	Association rule analysis, Éclat algorithm
Wang et al. [23]	1128 global maritime accidents during 2000–2019	Zero-inflated ordered probit (ZIOP) regression
Li et al. [24]	Unreported maritime accidents during 2000–2014 in Fujian waters	Multivariate imputation using chain equation
Wang et al. [25]	3484 global maritime accidents during 2010–2019	Hot spot analysis, outlier analysis
Vojković et al. [26]	Maritime grounding accidents in Adriatic Sea	Probabilistic-based BN
Liu et al. [27]	414 maritime accidents in China during 2013–2020	Data-driven BN, machine learning

Potential accident causes often differ depending on ship type and navigational waters. In some cases, a specific risk factor plays a decisive role. Ma et al. [9] focused on bulk carriers in Australian waters and ranked key factors influencing accident severity. Brandt et al. [28] emphasized weather conditions in accident risk prediction, while Luo and Shin [29] highlighted the influence of shipping market conditions. However, accidents are rarely the result of a single risk factor, and they are usually caused by the interaction of two or more risk factors. In cases where accident risk factors have been statistically recorded, corresponding databases are often established. For example, Gan et al. [30] constructed a knowledge graph to expand the factor database. Scholars have also applied various methods—such as Bayesian networks, complex networks, association rules and convolutional neural networks—to analyze these interactions. For instance, Liu et al. [27] employed network analysis to identify causal relationships among risk factors, and Deng et al. [17] built a complex network model incorporating human, ship, environmental, and management factors. As summarized in Table 1, the HFACS framework is one of the most widely adopted classification systems in maritime accident causation research. Originating from the aviation industry and later adapted to the maritime domain, it is valued for its hierarchical structure and systematic human factors orientation, providing a standardized foundation for cause categorization across different studies. Furthermore, two relevant IMO frameworks provide institutional reference for human factor analysis: the International Safety Management (ISM) Code (Resolution A.741(18)) [31], which sets out mandatory requirements for safety management and manning, and the List of Human Element Common Terms (Resolution A.884(21)) [32], which standardizes the terminology for human factor classification across member states. The classification system of HFACS aligns conceptually with these IMO instruments, providing institutional justification for the adoption of HFACS as the core analytical framework in this study.

In parallel, scholars have begun studying accident risk factors from a regional perspective, aiming to provide guidance for accident prevention in specific environments. For example, Huang et al. [15] applied weighted association rule mining to analyze maritime accidents in the Mediterranean and Black Seas. Ma et al. [7] developed a data-driven BN that combines human and organizational failures with environmental factors in Arctic waters.

Notably, an analysis of recent maritime accidents reveals that the causes have shifted from structural issues of the ship itself to the combined effects of human operation and ship-related issues, marking a transition from singular to multi-source causes. While many scholars have recognized the correlations between risk factors, such as Lan et al. [22], who used the Eclat algorithm to extract association rules from maritime total loss records with a particular emphasis on seafarers' unsafe acts, the correlation between data varies greatly depending on region, accident type, and recorded risk factors. Nevertheless, the critical role of crew-related factors in accident causes has been widely acknowledged. The above studies provide a broad foundation for understanding accident causation from multiple perspectives.

Despite the above contributions, three gaps remain to be addressed in terms of analytical framework and research methodology.

First, existing HFACS extensions that incorporate external conditions primarily frame external factors as environmental and vessel-related conditions, treating them as parallel antecedent events [7]. However, these extensions remain largely centered on physical and navigational conditions; scholarly attention to contributing factors linked to third-party stakeholders outside the core vessel operation chain remains relatively scarce [14,33]; while not always decisive, their effects merit targeted exploration in specific contexts. Official investigations by MAIB, EMSA and NTSB adopt a full-scope framework covering regulators, shore management, port authorities and third-party providers. This gap may

be primarily attributed to divergent research objectives that prioritize internal human and organizational safety factors as core analytical targets.

Second, BN-based studies map association rule analysis results into directed HFACS hierarchies [7,9]. Such models are built upon a preset hierarchical unidirectional causal structure. By contrast, institutional systemic investigations follow an open, multi-layered causal tracing logic: they identify contributing factors across multiple hierarchical levels (e.g., operational, managerial and regulatory), with no preset directional constraints. This forced directionality limits the characterization of cross-level co-occurrence patterns and mutual associations between contributing factors. Even purely data-driven BN studies are constrained by HFACS classification and inherit its linear logic [27].

Third, existing complex network analyses mainly use basic centrality metrics like degree, betweenness, and PageRank [13,17]. They lack a systematic distinction between different node roles, such as bridges that connect different contributing factor clusters and hub nodes that form the core of these clusters. This limits their ability to provide targeted diagnostic insights for safety interventions in co-occurrence network studies. As can be seen from the above systematic review of existing methodologies, these limitations are also shared by data-driven Chinese waterborne transportation accident studies, highlighting the necessity of establishing a more holistic analytical framework.

To address these gaps, this study develops an integrated framework based on 886 accident investigation reports from China MSA (2013–2023).

First, a hybrid deductive–inductive coding procedure combining grounded theory and the HFACS framework is adopted. This procedure yields 76 contributing factor sub-categories across five dimensions, including a dedicated external influence dimension that extends the conventional four-layer closed structure, thereby capturing disturbances from stakeholders such as illegal fishing, terminal mismanagement, and cargo misdeclaration that may be overlooked in existing frameworks.

Second, association rule analysis is then performed without preset hierarchical or directional constraints. It mines frequent co-occurrence patterns and strong cross-dimensional associations between contributing factors directly from raw data, avoiding the limitation of existing BN studies that forcibly map association rule results onto unidirectional causal hierarchies.

Third, an undirected weighted co-occurrence network of contributing factors is constructed using social network analysis methods. The undirected network structure itself addresses the forced unidirectional causality limitation inherent in BN models. For node-level analysis, nodes are evaluated from three dimensions of connection strength, criticality, and activeness to systematically identify cross-cluster bridging nodes and intra-cluster core hubs; this three-dimensional node assessment system compensates for the deficiency of existing complex network studies that rely on basic centrality metrics and lack systematic node role differentiation. This integrated approach offers a more holistic characterization of accident contributing factor co-occurrence patterns.

3. Principle of the Proposed Methodology

3.1. Overview of the Proposed Methodology

The purpose of this study is to characterize the interaction among various waterborne transportation accident causes. The proposed methodology can be viewed in Figure 1, in which all the work can be completed within four steps.

Step 1: Extraction and classification of accident causes. All waterborne transportation accident investigation reports are first collected to build the database. The contributing factor analysis sections are then extracted and processed through a hybrid HFACS-grounded theory coding procedure for systematic identification and conceptualization of accident

causes, yielding a five-dimension contributing factor classification framework consisting of unsafe acts, preconditions, unsafe supervision, organizational influences, and external influence factors. The five dimensions are further aggregated into two groups: crew-related causes (i.e., unsafe acts of crew) and non-crew-related causes (preconditions of unsafe behaviors, unsafe supervision, organizational influences, and external influence factors).

Step 2: Characterization of cause interactions via an undirected weighted social network. With accident causes as nodes, an edge is established between two nodes if the corresponding causes co-occur in the same investigation report (edge weight denotes co-occurrence frequency), forming an undirected weighted social network. Network nodes are subsequently assessed from three perspectives: criticality, activeness, and connection strength.

Step 3: Association rule analysis between crew-related and non-crew-related causes. Based on the two-group classification established in Step 1, association rules between crew-related and non-crew-related causes are extracted and evaluated using three metrics: support, confidence, and lift.

Step 4: Result discussion and countermeasure development. The analytical results are discussed, and targeted countermeasures for waterborne transportation accident prevention are proposed.

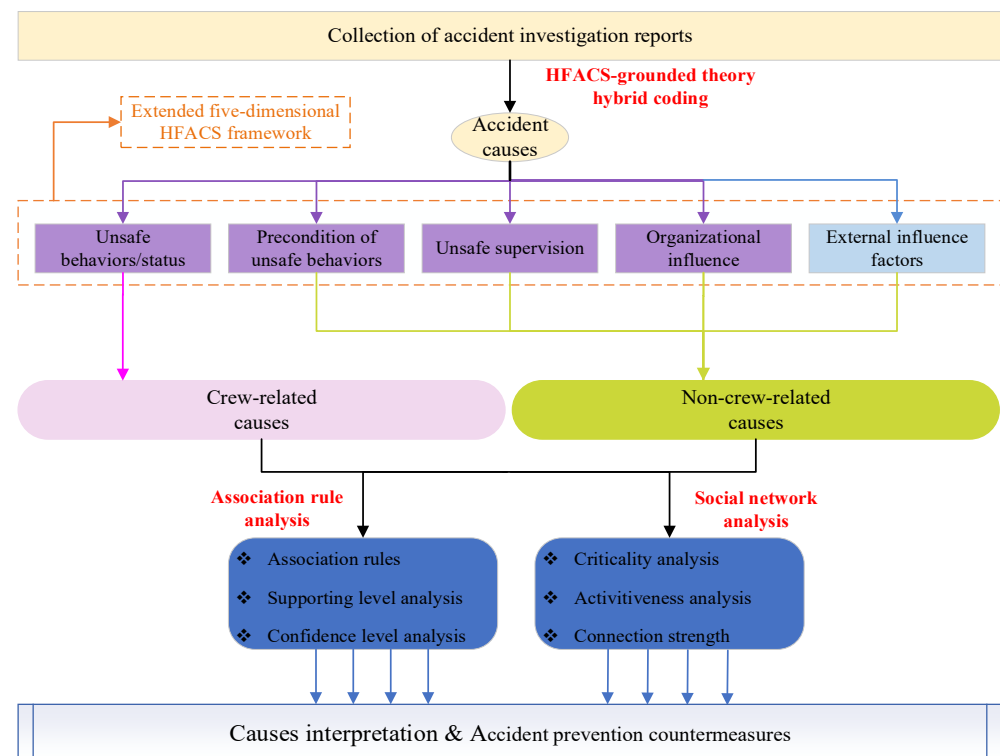


Figure 1. Workflow of the proposed methodology.

3.2. HFACS-Based Hybrid Accident Cause Coding

Grounded theory is a classic bottom-up qualitative method for processing textual data, first proposed by Glaser and Strauss [34]. In its classic form [35], it follows three standard coding stages: open coding, selective coding, and theoretical coding, and is widely used to refine concepts and extract core categories from unstructured text materials [36]. Qualitative analysis software such as NVIVO and ATLAS.ti are commonly used to assist coding implementation, and NVIVO 14 was used to code the accident causes in this study.

To avoid the fragmentation of purely inductive coding and maintain comparability with existing maritime accident research, this study adopts a hybrid deductive–inductive

coding strategy integrating grounded theory coding procedures with the classical HFACS framework. The third stage (theoretical coding) of classic grounded theory is replaced by an HFACS-guided integrated classification. The core process of the method is illustrated in Figure 2.

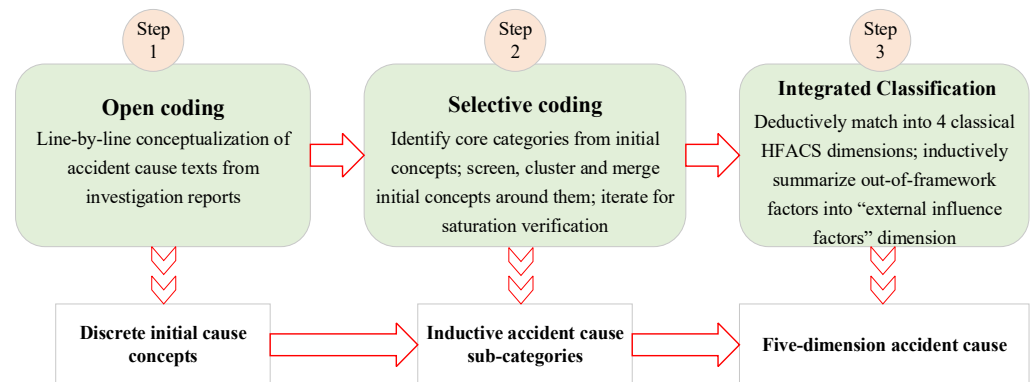


Figure 2. HFACS-based hybrid accident cause coding procedure.

Step 1: Open coding: Line-by-line conceptualization is performed on the original accident cause texts of 886 investigation reports, and discrete initial cause concepts are extracted by labeling descriptive phenomena in the texts.

Step 2: Selective coding: After core categories of accident causes are identified, initial concepts are screened, clustered, and merged around the core categories. After iterative theoretical saturation verification, final accident cause sub-categories are obtained inductively.

Step 3: Integrated classification: In the same classification process, most sub-categories are deductively matched into four classical HFACS dimensions as the basic classification framework; sub-categories beyond the HFACS scope (e.g., port management deficiencies, illegal behaviors of external stakeholders, insufficient navigational facilities) are inductively summarized into an independent “external influence factors” dimension simultaneously [37], forming the final five-dimension classification system.

3.3. Association Rules Analysis

Association rule analysis is widely regarded as an important data mining technology, which is frequently jointly applied with text mining to determine the correlation among different maritime accident causes. Since the association rule analysis was first proposed by Agrawal et al. [38], it has been widely applied to explore correlations among contributing factors across various industries [39–41]. A key reason for its popularity is its relatively low requirement on data volume and structure. The association rule analysis is mathematically described as follows.

A set is first induced as $I = \{I_1, I_2, \dots, I_n\}$, which is defined as an item set, and the elements in this set are defined as “items”. The length of an item set is equal to the number of items in the set. Meanwhile, a transaction database is also defined, which is presented as $T = \{T_1, T_2, \dots, T_m\}$. In a transaction database, T_i denotes a nonempty subset of I , and each transaction is marked by a unique ID. For instance, if X is an item set in I , then the support of X (denoted $S(X)$) can be obtained by

$$S(X) = P(X) = \frac{\text{sup}(X)}{|D|} \quad (1)$$

where $\text{sup}(X)$ is the number of X contained in D . If the support of an item set with k length is larger than the specified minimum support defined by the decision maker, then the item set is called a frequent k -item set.

In practice, the association rules represent the correlation between two different item sets; thus, another item set Y in I is needed. As a result, $X \rightarrow Y$ can be used to represent the association rule between X and Y ($X \in I, Y \in I$, and $X \cap Y \neq \emptyset$), in which X is defined as the left-hand side (LHS), while Y is called the right-hand side (RHS). The connection strength of association rule $X \rightarrow Y$ is generally assessed in terms of support, confidence, and lift, respectively, which can be valued by means of data mining algorithms, such as the FP-Growth algorithm and Apriori algorithm.

(1) Support

In association rule analysis, the support is the probability of the item set I containing X and Y simultaneously, which can be obtained by

$$\text{sup}(X \rightarrow Y) = P(X \cup Y) \quad (2)$$

In practice, the minimum support is defined by the users according to the specific scenarios, which is generally used to select association rules.

(2) Confidence

The confidence of a specific association rule $X \rightarrow Y$ refers to the ratio of the item set containing X and Y and the item set containing X , which can be calculated by

$$\text{Con}(X \rightarrow Y) = P(Y/X) \quad (3)$$

In practice, the minimum confidence is defined by the users according to the specific scenarios, which implies the minimum reliability of the association rule. In addition, the association rules that satisfy both minimum support and minimum confidence are regarded as strong association rules.

(3) Lift

The lift of a specific association rule $X \rightarrow Y$ is the ratio of the confidence of $X \rightarrow Y$ to the probability of Y contained in the item set, which can be obtained by

$$\text{Lif}(X \rightarrow Y) = P(Y \setminus X) / P(Y) \quad (4)$$

The lift is also used to evaluate the reliability of the association rules, which is similar to confidence. Therefore, the lift can be regarded as a supplemental indicator of confidence. According to Yang et al. [42], the critical value of lift is usually set as 1, which means that the association rules with lift values larger than 1 are considered as being valid; otherwise, the association rules are invalid.

The key to conducting association rule analysis is to identify the frequent item sets; for this purpose, the FP-Growth algorithm is used in this study to mine the frequent item sets. The general principle of the FP-Growth algorithm is presented in Figure 3.

3.4. Social Network Analysis

According to the description in Section 3.1, the network developed in this study is an undirected weighted social network, which is represented by $G = (V, E)$. $V = \{v_1, v_2, \dots, v_M\}$ and $E = \{e_1, e_2, \dots, e_N\}$ denote the sets of nodes and edges, respectively. As a result, the $G = (V, E)$ can be described by an adjacency matrix with a volume of $M \times N$, which is denoted by A . The elements contained in the adjacency matrix are determined by

$$A_{ij} = \begin{cases} a_{ij} \times w_{ij} & i \leftrightarrow j \\ 0 & \text{else} \end{cases} \quad (5)$$

where $a_{ij} = 1$ in case of accident cause i and j simultaneously appearing in the same accident investigation report; otherwise, $a_{ij} = 0$. w_{ij} is defined as the weight of the edge connecting i and j , which indicates the connection frequency between i and j . In this study, the connection strength of a node in the social network is defined as

$$T_w(i) = \sum_{i,j \in V} w_{ij} \quad (6)$$

In addition, the number of edges connected to node (accident cause) i in the developed network is defined as the degree of node i in this study, which is denoted by $d(i)$. It is noted that the degree of a node just represents the influencing range, not the significance of the influence.

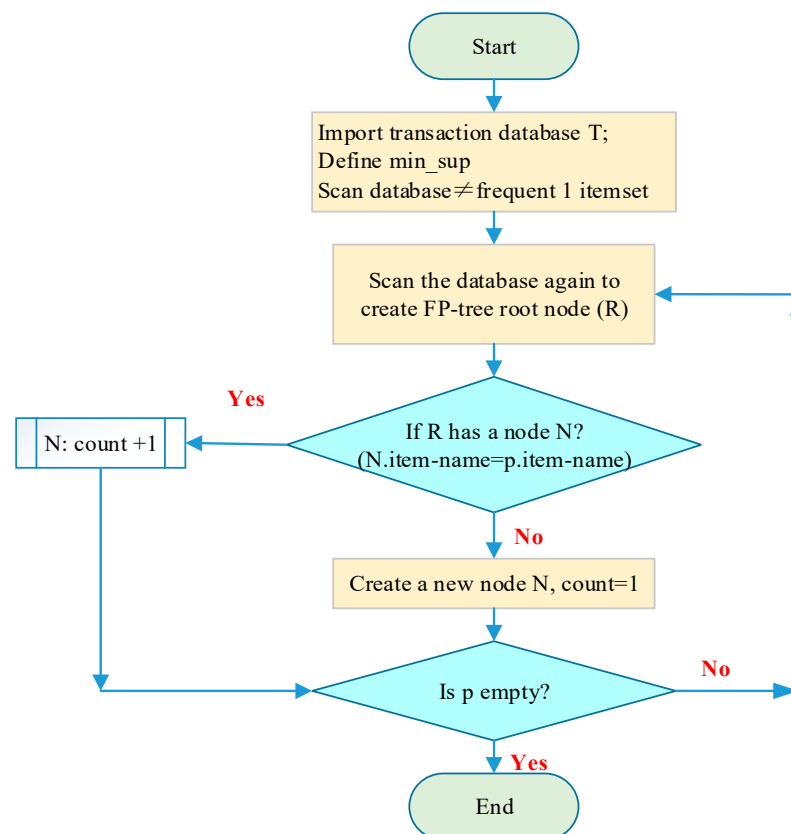


Figure 3. Flowchart of conducting FP-Growth algorithm.

Based on the basic parameters and structure of the developed social network, the accident causes extracted by means of grounded theory analysis can be assessed through the following indicators.

(1) Betweenness centrality

In social network analysis, betweenness centrality is defined as the number of shortest paths between all pairs of nodes that pass through a target node. It is commonly used to characterize the mediating role of a node in the entire network. Mathematically, the betweenness centrality is calculated by

$$B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (7)$$

where $\sigma_{st}(i)$ is the number of shortest paths passing node i between nodes s and t , and σ_{st} denotes the total number of shortest paths between s and t .

(2) Eigenvector centrality

Eigenvector centrality can be applied to assess the criticality of a node within a network, which is similar to the role of closeness centrality. However, the advantage of eigenvector centrality over closeness centrality is that its calculation incorporates the criticality of adjacent nodes, a dimension ignored by closeness centrality. The eigenvector centrality can be obtained by

$$E(i) = x_i = c \sum_{j=1}^N a_{i,j} x_j \quad (8)$$

where x_i denotes the importance of node i , c is a coefficient, and $a_{i,j} = 1$ only if nodes i and j are connected; otherwise, $a_{i,j} = 0$.

(3) Structural hole

Structural hole theory, originally proposed by Burt in 1992, conceptualizes structural holes as non-redundant connections between nodes in a network. Specifically, a structural hole exists when two neighbors of a given node are not directly connected to each other; the focal node thus occupies a brokerage position by bridging disconnected groups. In accident causation networks, this metric captures the extent to which a risk factor links otherwise disconnected clusters of contributing factors with minimal overlap among its connections. According to Burt, the structural hole of a social network can be evaluated by four indicators: effective size, efficiency, constraint, and hierarchy. In this study, the effective size would be selected to represent the structural hole, which is obtained by invoking the calculation module embedded in the software Ucinet 6.755 (32-bit).

(4) Clustering coefficient

The clustering coefficient of a node measures the probability of forming a triangle (interconnection) between its neighboring nodes, reflecting the local density of the network. Generally, the clustering coefficient can be calculated by

$$\delta(i) = \frac{2E_i}{k_i(k_i - 1)} \quad (9)$$

where E_i is the number of actual connections between node i and its adjacent nodes, k_i is the number of adjacent nodes of node i . Equation (10) applies to the social network without being weighted. However, the social network developed in this study is a weighted social network; thus, the nPairs-based clustering coefficient is introduced to evaluate the clustering of nodes within the developed social network, which is expressed as

$$\delta_p(i) = \frac{T_w(i)}{0.5 \times k(k - 1)} \quad (10)$$

where k is the number of adjacent nodes of node i , and $T_w(i)$ can be obtained by Equation (6). Actually, $0.5 \times k(k - 1)$ is the value of the total number of node pairs.

Beyond the node-level metrics introduced above, connection strength is employed to characterize the pairwise associative strength between accident contributing factors. Following the definition of Qiao et al. [43] and adapted to the undirected weighted co-occurrence network in this study, connection strength represents the weight of an edge linking two nodes, reflecting how frequently two factors co-occur across accident cases; higher edge weights indicate stronger co-occurrence patterns between the corresponding factors.

Building on this, the network is evaluated across three dimensions: connection strength, as well as criticality and activeness. Each of the three dimensions is operationalized via a distinct network metric outlined above, with detailed definitions summarized in Table 2.

Table 2. Aspects used to assess network nodes.

Aspects	Indicator	Description
Connection strength	Degree	Nodes with high degree have more connections with other nodes in the co-occurrence network, reflecting higher co-occurrence frequency of the corresponding accident cause.
	Connection degree	As the weighted version of the degree indicator, a higher connection degree value represents stronger co-occurrence association strength between accident causes.
Criticality	Eigenvector centrality	Nodes with high eigenvector centrality have stronger global influence in the network: their value is determined by the importance of their adjacent nodes.
Activeness	Betweenness centrality	Nodes with high betweenness centrality act as core bridges connecting different co-occurrence clusters of contributing factors at the global network level.
	Structural hole	Structural hole analysis identifies nodes occupying non-redundant connection positions in the co-occurrence network. A higher structural hole value (measured by effective size) indicates more non-redundant connections of the node, and its unique connection hub attribute is more prominent.
	Clustering coefficient	Nodes with higher clustering coefficients indicate closer co-occurrence associations among their neighboring contributing factors, reflecting the local aggregation characteristic of co-occurrence relationships.

4. Data Collection and Cause Extraction

4.1. Data Collection

In this study, the waterborne transportation accident investigation reports issued by China MSA during 2013–2023 are collected, which are accessed from the official website of China MSA at <https://www.msa.gov.cn> (accessed on 21 March 2026). As a result, there are a total of 886 accident investigation reports collected and considered as the database of this study. For each accident investigation report, the following information is contained according to the accident investigation regulation issued by the Ministry of Transport of China.

- (1) The general information and data of ships and facilities involved in the accidents, including the management aspect of the accidental ships.
- (2) The basic information about the accidents, such as date, time, location, sea condition, and accident damage.
- (3) The description of the accident process in detail, generally from the departure of the accidental ships to the occurrence of accidents.
- (4) The description of search and rescue at sea.
- (5) Accident causes identification and analysis, including safety tips to prevent similar accidents in the future.
- (6) The division of accident liability and its basis.

This study focuses on the co-occurrence analysis of accident causes; thus, only the content of the “accident causes identification and analysis” section (Item 5) is extracted from each report as the coding corpus. All 886 reports are compiled in accordance with unified national accident investigation specifications, and the structure of the cause analysis section is standardized, which ensures the comparability of the coding texts. The extracted cause texts are imported into NVIVO 14 for subsequent coding analysis. The whole coding work is conducted in Chinese based on the original report texts, and the final classification results are translated into English for presentation.

In the database of 886 accident investigation reports, the accident type distribution is presented in Figure 4. It should be noted that the number of accidents presented in Figure 4

is just the general description of the database in this study. In addition, the accident type “other” contains mainly occupational injuries of the crew on board the ships.

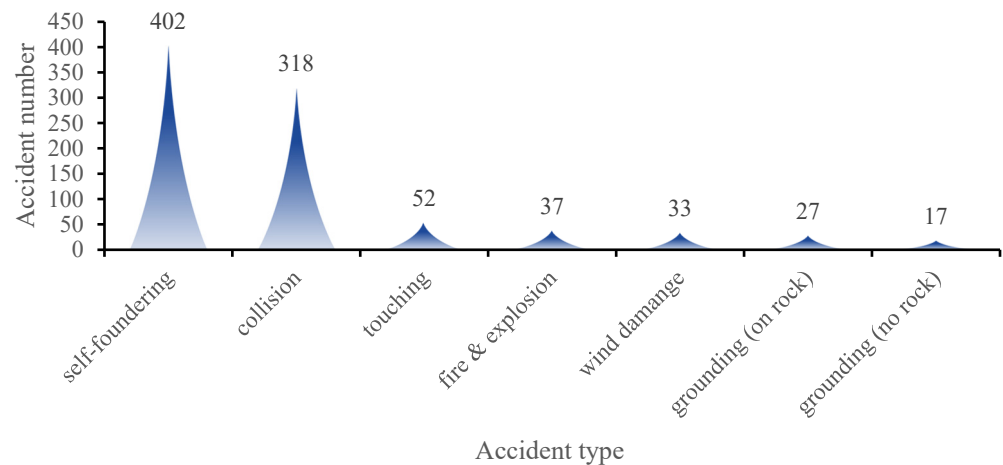


Figure 4. Accident types involved in the database.

4.2. Accident Cause Coding and Classification

Following the hybrid deductive–inductive coding method described in Section 3.2, the extracted accident cause texts were systematically coded using NVIVO 14. Part of the coding procedure is illustrated in Figure 5.

The initial coding framework and a preliminary coding manual were first developed by a single trained researcher. The work was grounded in the classical HFACS framework and open coding of 50 randomly selected reports. The preliminary rulebook included draft operational definitions, inclusion–exclusion criteria, and conceptual boundaries for preliminary categories. To mitigate subjective bias from single-researcher coding and refine the classification system, an expert consensus validation procedure was adopted. Two senior experts with more than 10 years of experience in maritime safety management and accident investigation were invited to independently review two aspects: (1) the rationality of category definitions and hierarchical settings in the preliminary rulebook; and (2) the coding results of another 30 randomly selected reports, to verify the applicability of the rulebook and identify ambiguous categorization cases. Discrepancies and ambiguous categorizations were discussed in a joint meeting until full consensus was reached, and the coding rulebook and classification framework were revised accordingly to form the finalized version. All 886 accident reports were then formally coded by this same researcher following the finalized rulebook.

Through open coding, 139 initial cause concepts were extracted from the textual corpus by line-by-line conceptualization. In the selective coding phase, core accident categories were first identified; then, the initial concepts were screened, clustered, and merged around these core categories, yielding 76 specific accident cause sub-categories inductively. To verify theoretical saturation, a separate set of 30 accident investigation reports was reserved as an independent validation set before any framework development. This subset was not involved in rulebook construction or expert calibration. When the complete coding procedure was applied to these 30 reports, no new core categories or sub-categories emerged, confirming that theoretical saturation had been reached.

Based on the 76 inductively generated sub-categories, integrated classification was conducted using the classical HFACS framework as a reference: most sub-categories were deductively matched into the four classic dimensions of the HFACS framework, while risk factors falling outside the scope of HFACS (such as port operation and management deficiencies, illegal behaviors of external stakeholders, and insufficient public navigational

facilities) were inductively grouped into an independent “external influence factors” dimension. Following this hybrid coding procedure, all accident causes were systematically identified and organized into the final five-dimension classification framework.

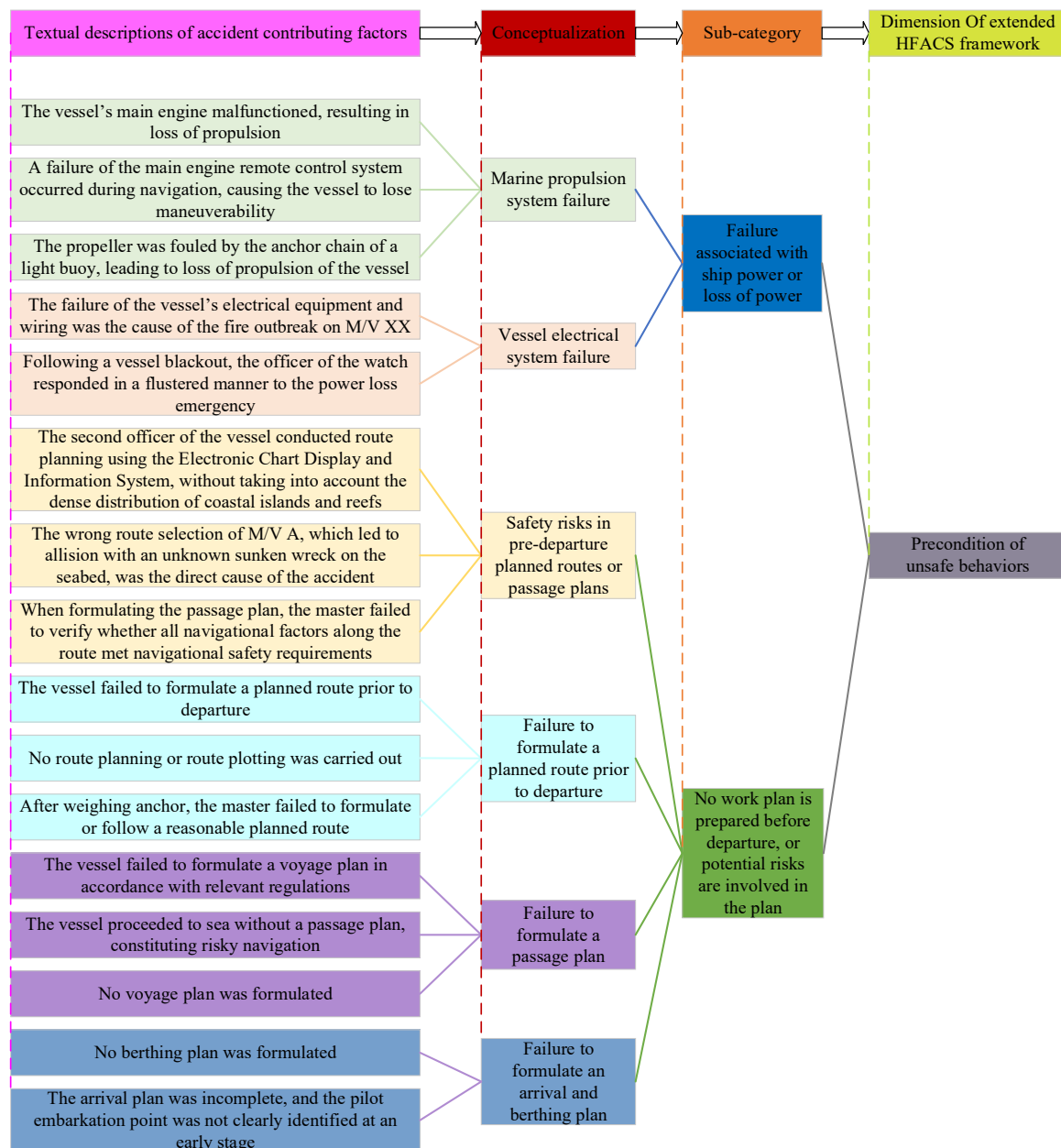


Figure 5. Example of the hybrid coding process for accident contributing factors.

4.3. Results of Cause Extraction

According to the method described in Section 4.2, there are 76 accident causes identified in this study, which are summarized in Table 3.

Table 3. Results of accident cause extraction.

Code	Causes
Crew-related causes (unsafe behaviors or status of crew on board the ships)	
U1	The crew on duty fails to maintain proper lookout.
U2	Failure to fully evaluate the potential risks of collision, grounding or foundering.

Table 3. Cont.

Code	Causes
U3	Failure to comply with the standard operational procedures on board the ship.
U4	Failure to use the safety speed.
U5	Underestimating the influence of environmental conditions during navigation.
U6	Failure to pilot the ships with caution.
U7	Inappropriate operations on board the ships.
U8	Low emergency response capacity of the captain.
U9	Underestimating the influence of environmental conditions before departure.
U10	Failure to maintain cautious navigation.
U11	Inappropriate cargo handling.
U12	Failure to use good seamanship to maneuver the ship.
U13	Violating regulations or rules designed for navigation safety.
U14	Failure to conduct preparation for cargoes before departure.
U15	Low sense of responsibility of the crew on duty.
U16	Violating in terms of operation.
U17	Failure to identify risks in a timely manner and take effective measures.
U18	Failure to correctly use the navigational facilities, or these facilities are unavailable.
U19	The crew on duty does not know the planned route, or the planned route is not followed.
U20	Failure to select the proper anchorage.
U21	Failure to keep safe clearance with other ships, shore, and other obstructions.
U22	Failure to comply with CLOREGS.
U23	Failure to verify the effectiveness of risk management measures.
U24	Emergency response of crew is inappropriate or inexperienced.
U25	Failure to correctly conduct the handover.
U26	Failure to report to the MSA after the accidents.
U27	The operators conducting special operations on board are not qualified.
U28	Insufficient crew on duty or no crew on duty.
U29	Crew is not familiar with the operation of relevant equipment on board.
U30	The suitability for being delivered is not verified before departure.
U31	Poor cargo management during the ship's voyage.
Non-crew-related causes (preconditions for unsafe behaviors)	
P1	Poor communication.
P2	No work plan is prepared before departure, or potential risks are involved in the plan.
P3	Part of the hull structure (or modification) does not comply with regulations.
P4	The ship is equipped with insufficient life-saving equipment or no life-saving equipment.
P5	Crew on duty is influenced by alcohol.
P6	Poor technical status or poor maintenance of the ships.
P7	Violation of the fishery ships involved in ship collision.
P8	Illegal installation of fishery production facilities.
P9	Rough sea with strong wind.
P10	Complex navigation environment.
P11	Poor visibility.
P12	Lack of caution towards unfamiliar waters.
P13	Mechanical failure on board.
P14	Strong tide.
P15	Overload or suspected overload.
P16	Incompetent crew.
P17	Not familiar with the navigational environment.
P18	Fatigue.
P19	Failure associated with ship power or loss of power.
P20	Failure to timely obtain accurate meteorological and hydrological information.

Table 3. *Cont.*

Code	Causes
Non-crew-related causes (unsafe supervision and management)	
S1	Poor management on board the ships.
S2	Poor risk awareness of the captain during daily on-board management.
S3	The operation of the ship is illegal due to invalid certificates.
S4	The shipping companies fail to provide sufficient and competent crew on board.
S5	The actual operator directs the ship to transport illegally.
S6	Intentional closure of AIS by ships, or use of false AIS, or AIS malfunction.
S7	The captain's command authority on board is restricted.
S8	The shipping companies fail to complete procedures for the entry and exit of ships.
S9	The shipping companies fail to know the status of the ships.
Non-crew-related causes (organizational influence)	
O1	The company has not effectively implemented its safety management responsibilities.
O2	Ship owner and operator ignored safety management.
O3	Failure to provide effective and fully shore-based support.
O4	Failure to prepare or implement a training plan.
O5	The company's safety management system is incomplete.
O6	The company did not provide sufficient paper nautical charts for the ships.
O7	The company's management personnel are not qualified.
O8	The company has not organized emergency drills for a long time.
O9	Crew has a low sense of safety responsibility.
Non-crew-related causes (external influence)	
E1	Illegal ships are employed to participate in offshore activities.
E2	Illegal operation of the terminal without safe berthing conditions.
E3	Poor cargo handling conditions of the terminal.
E4	Insufficient navigational facilities.
E5	Poor safety management system of the terminal.
E6	The shippers falsely report the cargoes to be delivered.
E7	Illegal offshore activities.

5. Analysis and Discussion of Accident Causes

According to the basic principle of the proposed methodology stated in Section 3.1, the accident causes are considered as the nodes, and different nodes are connected to each other if these nodes appear simultaneously in the same accident investigation report. As a result, a social network can be developed as shown in Figure 6. It should be noted that E1–E7 in Table 3 are represented by 1–7 in Figure 6; meanwhile, O1–O9 in Table 3 are represented by 8–16, P1–P20 in Table 3 are represented by 17–36 in Figure 6, S1–S9 in Table 3 are represented by 37–45 in Figure 6, and U1–U31 in Table 3 are represented by 46–76 in Figure 6.

5.1. Interaction Between Crew-Related Causes and Other Causes

Crew-related factors are widely regarded as the main direct causes of waterborne transportation accidents [44]. Therefore, the interaction between crew-related causes and other causes would be investigated first based on the principle of association rule analysis described in Section 3.3. For this purpose, the RHS of association rule analysis is set as the crew-related accident causes, and the LHS contains the accident causes associated with both crew-related and non-crew-related causes. Notably, all three thresholds mentioned above are manually set according to the specific research scenario and data mining objectives [45–47]. Given the substantial imbalance in sample sizes across accident categories (ranging from 17 to 402 incidents), a differentiated threshold strategy was adopted

rather than applying uniform parameters to all datasets. A baseline threshold calibration procedure was conducted by testing multiple combinations of minimum support (ranging from 0.01 to 0.24) and minimum confidence (ranging from 0.05 to 0.30) for each accident type. The final thresholds, as presented in Table 4, were selected at the inflection point of the rule-count decline curve, which balances the richness of potential co-occurrence patterns and the filtering of random noise.

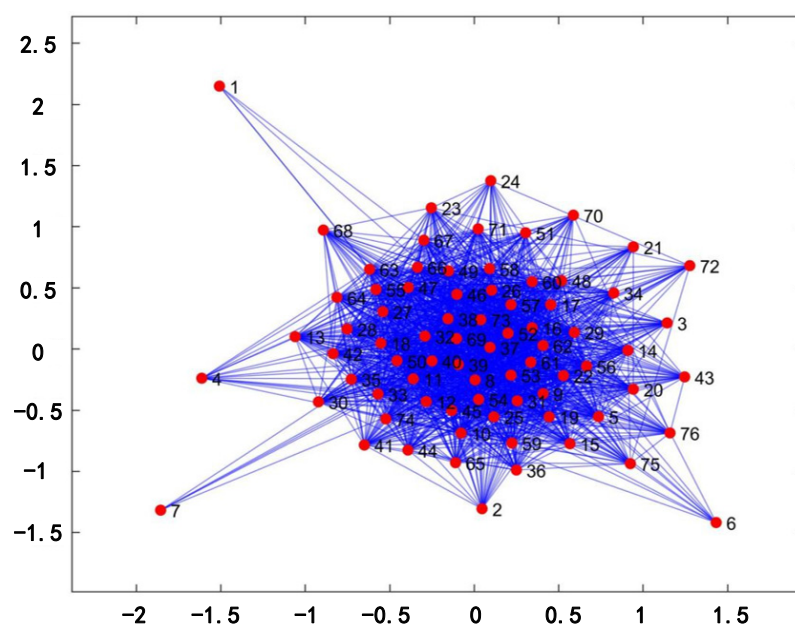


Figure 6. Topological structure of the developed social network.

Table 4. Parameter settings for association rule mining by accident type.

	Collision	Self-Foundering	Touching	Grounding (on Rock)	Grounding (No Rock)	Wind Damage	Fire and Explosion
Number of transactions	318	402	52	27	17	33	37
Mini_sup	0.04	0.02	0.02	0.04	0.06	0.04	0.04
Mini_con	0.10	0.10	0.10	0.10	0.20	0.10	0.10
Mini_lift	>1	>1	>1	>1	>1	>1	>1

The relatively low confidence threshold is aligned with the exploratory nature of this study. Since waterborne transportation accidents typically result from multi-factor coupling rather than being driven by a single factor, a lower confidence threshold helps retain weak but meaningful co-occurrence combinations. All retained rules are filtered by a lift value greater than one to ensure positive correlation, and the core analysis is consistently based on high-support, high-lift association rules.

To verify that the core findings are not contingent on a single arbitrarily selected threshold combination, threshold robustness checks were conducted using three sets of proportional deviations from the baseline values: -20% (looser), $+20\%$ (stricter), and $+50\%$ (stricter). Each deviation was applied simultaneously to both minimum support and minimum confidence, while the lift threshold (>1) remained constant across all test groups as a uniform validity filter. This asymmetric deviation design was adopted intentionally. The baseline thresholds were already set at the inflection point of the rule-count decline curve to balance pattern richness and noise filtering. A -50% looser setting was not tested, as it would introduce an excessive volume of low-frequency, low-informative random co-occurrence pairs and fall beyond the meaningful exploratory scope of this study. Across

all seven accident types, the core association rules with high support and high confidence remain consistently identifiable within each accident type across all parameter groups, and the frequency-based ranking of key contributing factors in strict rules shows no material shift among top positions for each accident category. While the total number of generated rules naturally varies with threshold stringency, these quantitative changes do not alter the qualitative interpretation of core co-occurrence patterns. This supports that the main findings are robust to reasonable threshold adjustments.

Finally, 192 association rules are generated for grounding (on rock) accidents, 302 association rules are generated for touching accidents, 133 association rules are generated for wind damage accidents, 162 association rules are generated for grounding (no rock) accidents, 149 association rules are generated for fire/explosion accidents, 451 association rules are generated for collision accidents, and 397 association rules are generated for self-foundering accidents. The important association rules are presented in the form of a grouping matrix diagram, which is illustrated in Figure 7. Each row in Figure 7 represents RHS, which denotes the crew-related accident causes; while each column represents LHS, which contains the contributing factors for the crew-related accident causes. In Figure 7, the depth of the balloon color indicates association rules with higher confidence, while balloon size indicates the support level of association rules. Generally, the association rule matrix shows that various contributing factors from the LHS columns are broadly associated with crew-related accident causes in the RHS rows, suggesting that crew unsafe behaviors do not occur in isolation but typically co-exist with multiple preceding preconditions.

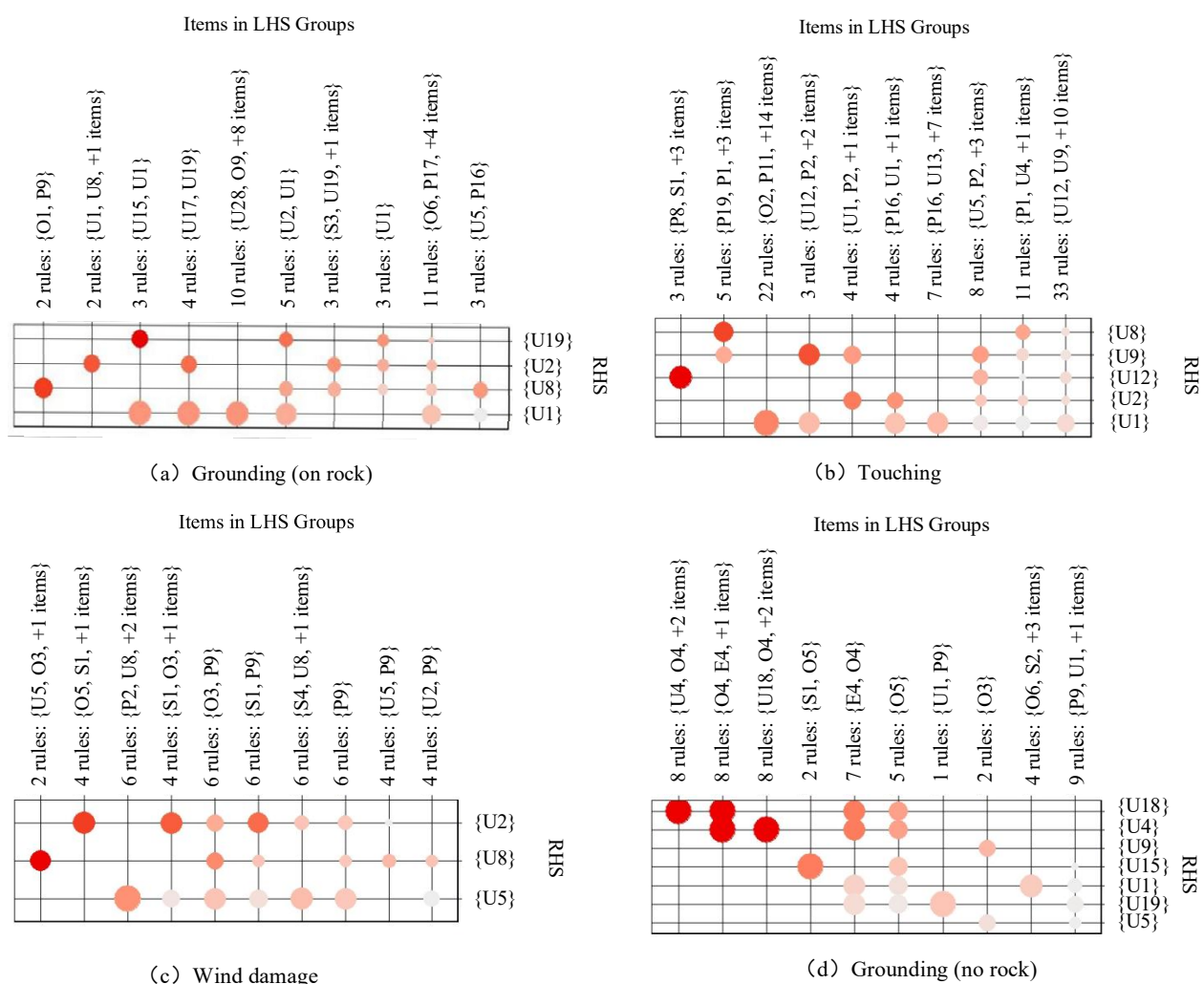


Figure 7. Cont.

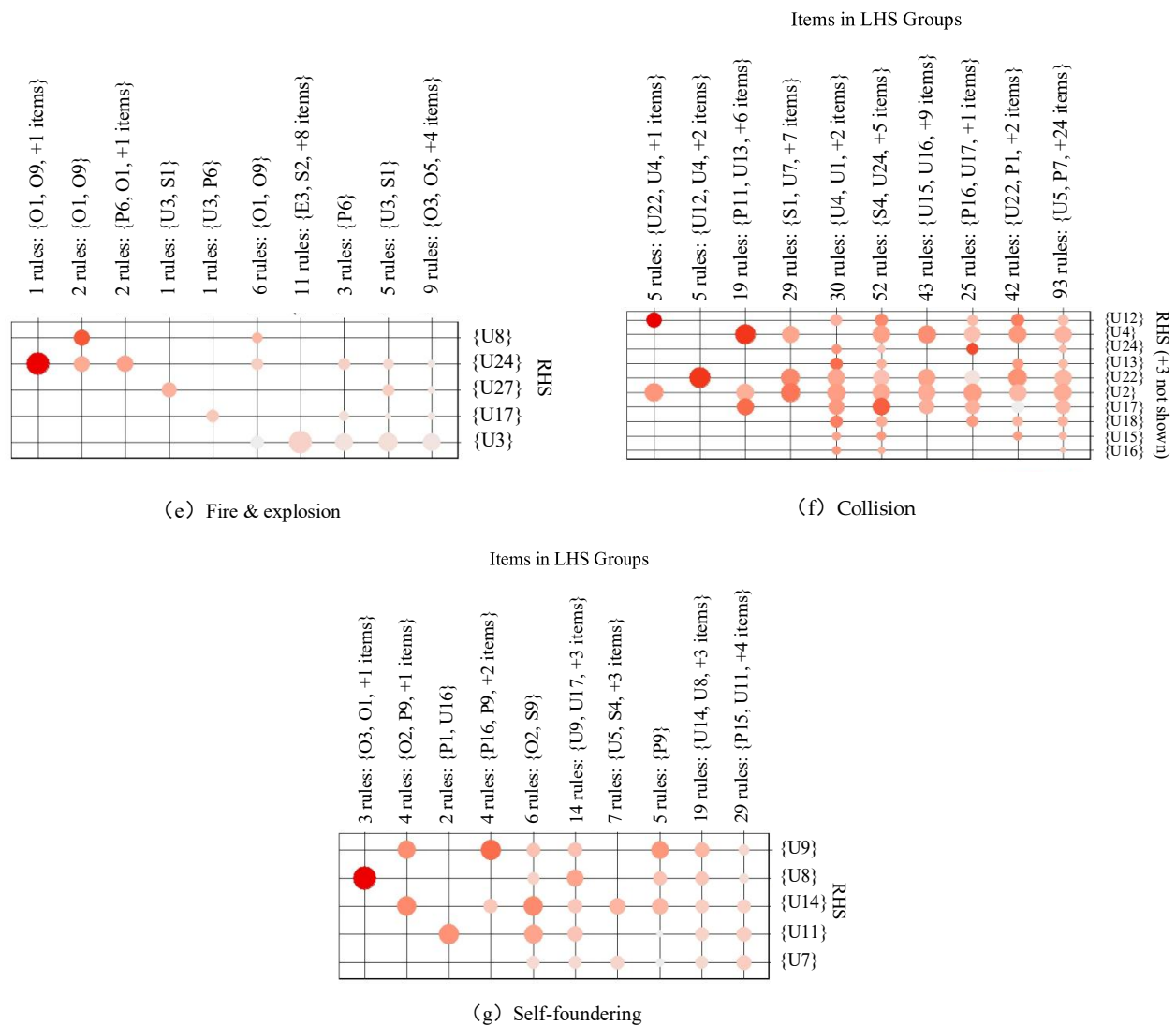


Figure 7. Association rules analysis in terms of support and confidence.

For the grounding (on rock) accidents, high-frequency association rules predominantly center on factor U1 (failure of the duty crew to maintain proper lookout), as shown in Figure 7a. This pattern suggests that this factor merits priority attention in the safety governance of grounding (on rock) accidents. A similar pattern is observed for touching accidents, whose strong association rules are presented in Figure 7b. Furthermore, for touching accidents, the rule “{P8, S1 => U12}” is another notable finding, characterized by both high support and high confidence. Correspondingly, factors related to poor seamanship and on-board management warrant close attention in safety practice for this accident type. In addition, factor U9 (underestimating the influence of environmental conditions) also shows strong co-occurrence patterns with other contributing factors in the association rules of touching accidents. Figure 7d presents the strong association rules for grounding (no rock) accidents. Nearly all high-strength association rules center on three core accident causes: failure to fully evaluate potential accident risks (U2), the influence of adverse environmental conditions (U5), and the low emergency response capacity of the captain (U8). The rule “{U5, O3 => U8}” has the highest confidence, indicating a strong co-occurrence association among adverse environmental conditions (U5), insufficient shore-based support (O3), and insufficient captain emergency response capacity (U8). Figure 7d presents the strong association rules for the grounding (no rock) accidents. It can be observed that U4 (failure to use a safe speed) and U18 (failure to

correctly use navigational facilities) are the most prominently co-occurring contributing factors in this type of accident. In addition, the training plan for the crew on board (O4) warrants close attention in the safety governance of grounding (no rock) accidents. As shown in Figure 7e, the most notable association rule for fire and explosion accidents is “{O1, O9 => U24}”, which indicates a strong co-occurrence association among weak corporate safety management responsibility awareness (O1), low crew safety responsibility awareness (O9), and poor crew emergency response performance (U24). When it comes to collision accidents, the results are presented in Figure 7f. It can be observed that the crew-related causes are involved in a greater number of strong association rules compared with other accident types, forming more diverse co-occurrence combinations with both crew and non-crew accident causes. This suggests a relatively more diverse co-occurrence structure of contributing factors for collision accidents within the current sample. Finally, the strong association rule results for the self-foundering accidents are shown in Figure 7g. The most prominent association rule is “{O1, O3 => U8}”. This rule indicates that factor U8 (insufficient captain emergency response capacity) appears with high frequency in the strict rules for self-foundering accidents, and that two shore-related factors—corporate safety management (O1) and shore-based support (O3)—present a strong co-occurrence association with this capacity factor.

In addition, lift is another core evaluation metric for association rules, which is valued by the FP-algorithm described in Section 3.3. Accordingly, the association rules with the highest lift value for each type of accident are listed in Table 5. It is notable that the lift values of association rules involved in the collision and self-foundering accidents are relatively low, even though the sample sizes of these two accident types are obviously larger than those of other accident types in the dataset. By identifying core co-occurrence combinations of contributing factors, lift analysis can provide directional reference for formulating targeted accident prevention strategies. Taking the touching accident association rule “{S3, U1} => {U17}” as an example, proper lookout maintenance (U1) and legal ship operation (S3) show a strong co-occurrence association with the contributing factor of failed emergency avoidance (U17), which provides a key focus for daily safety inspection and prevention work.

Table 5. Association rules with highest lift in terms of different accident types.

Accident Type	Association Rule	Lift
Collision	{P1, U13} => {U4}	1.85
Self-foundering	{P9, P16, S3, U8} => {U9}	2.74
Fire and explosion	{S1, U3} => {U27}	3.47
Grounding (no rock)	{E4, U4} => {U18}	8.50
Grounding (on rock)	{P12, U1} => {U28}	6.00
Touching	{S3, U1} => {U17}	8.67
Wind damage	{O3, U5} => {U8}	2.69

5.2. Connection Strength Analysis

Building on the undirected weighted co-occurrence network framework defined in Section 3.4, node-level structural attributes are analyzed across three dimensions: connection strength, criticality, and activeness.

To focus the discussion on structurally prominent contributing factors and derive targeted safety implications, the Pareto principle is adopted as a heuristic criterion for core node prioritization. As a well-established approach for priority screening in safety science [48] and maritime research [49], this principle guides the selection of a small subset of nodes with the most salient topological properties, which preserves analytical focus while ensuring comprehensive coverage of the core structural characteristics of the co-occurrence

network. This uniform screening rule is applied to all network metrics across the three analytical dimensions. For the 76 contributing factor sub-categories in the classification framework, the top 20% of nodes—equivalent to 16 nodes ($76 \times 20\% = 15.2$, rounded up)—are selected as the core analytical set. Supplementary checks with alternative cut-offs (top 15% and top 25%) show high consistency in the set of core nodes, verifying the robustness of this screening threshold. Accordingly, the top 16 nodes ranked by each metric presented in Table 2 are discussed in detail in subsequent sections.

According to the analysis in Section 3.4, the connection strength of nodes (accident causes) would be analyzed by the network parameters of degree and connection degree. In terms of connection strength analysis, the degree and connection degree of a node are calculated according to the methods described in Section 3.4, and the results are presented in Figure 8 and Figure 9, respectively. According to the definition, the degree is an unweighted concept, as shown in Figure 8. U17 (failure to identify risks in a timely manner and take effective measures) is determined as the node connected by the largest number of other nodes, and P16 (incompetent crew) and S1 (poor management on board the ships) are ranked as the second and third, respectively. According to the results presented in Figure 8, among the top 20% of contributing factors ranked by degree centrality, 50% belong to the category of “unsafe behaviors and states of on-board crew”, and 25% fall into the category of “unsafe supervision and management”. In addition, external influence accident causes are not observed in the high-centrality ranking of Figure 8.

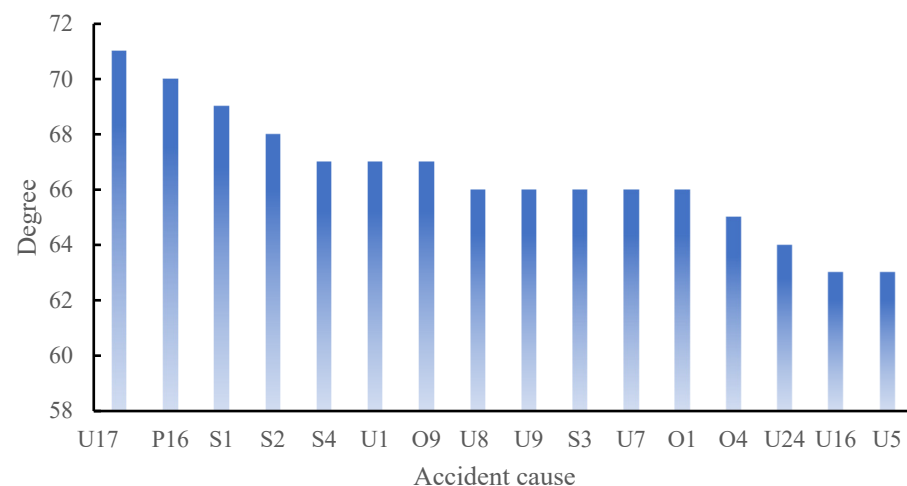


Figure 8. Top accident causes in terms of degree.

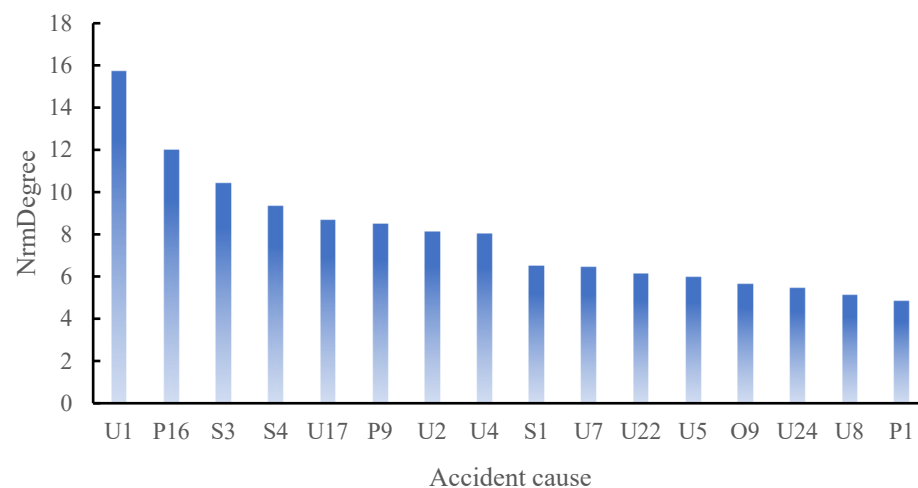


Figure 9. Top accident causes in terms of connection degree.

According to the definition of degree, it can only roughly reflect the number of connections of a node and cannot well represent actual connection strength since edge weights are not considered. Therefore, we further calculated the weighted connection degree of nodes, and the results are presented in Figure 9. Obvious differences can be observed by comparing Figure 9 and Figure 8: the node with the highest degree centrality (U17) ranks fifth in connection degree; while U1 (the crew on duty fails to maintain proper lookout), which ranks sixth in degree centrality, ranks first in connection degree. Since connection degree reflects the weighted co-occurrence frequency of factors, it is more suitable for measuring the association strength between contributing factors. Accordingly, U1 can be regarded as the node with the strongest connection strength in the network. Another notable node is P16, which ranks second in both degree centrality and connection degree. The above results can provide priority references for waterborne transportation safety management in China: high connection strength nodes, including P16 (incompetent crew) and U1 (improper lookout), can be taken as the core focus of daily management. For these two types of contributing factors, traditional management modes can be combined with technical means such as intelligent monitoring and advanced communication systems to assist daily management.

5.3. Criticality Analysis

According to Table 2 in Section 3.4, the criticality analysis of nodes would be conducted by eigenvector centrality, and the results are illustrated in Figure 10. It is interesting to find that the results presented in Figure 10 are similar to those in Figure 8. Based on the definition of criticality, the nodes with higher values of criticality should be paid more attention to prevent the occurrence of accidents. U17 (failure to identify risks in a timely manner and take effective measures) ranks first in criticality, indicating that this factor occupies a core position in the overall co-occurrence network, which can provide reference for the construction of accident early warning systems. Actually, the early warning can be divided into two groups: warnings from the crew on duty on board the ships, and warnings from shore bases, such as Vessel Traffic System (VTS) and shipping companies. In this study, the accident cause of U17 is mainly associated with the warnings from the crew on duty. Combined with the connection strength analysis in Section 5.2, the connection strength of U17 ranks fifth. This indicates that, different from top nodes with wide cross-category co-occurrence coverage, the co-occurrence associations of U17 are mainly concentrated among a small number of closely related factors, so the entry points for targeted management are clearer. Generally, there are two paths for timely risk identification and emergency response: relying on highly competent on-board crew, and relying on sound on-board safety management. However, incompetent crew (P16) ranks second in both criticality (Figure 10) and connection strength (Figure 9); single-dimensional optimization targeting crew capacity is relatively difficult to implement. Therefore, a better way to control U17 may lie in the improvement of management on board the ships, which can be achieved by employing a highly qualified captain.

In addition, the “incompetent crew” (P16) is also valued by high criticality according to Figure 10; theoretically, it is necessary to eliminate the incompetent crew as much as possible in the near future. However, “incompetent crew” is also valued by high connection strength according to Figure 9. Therefore, it is reasonable to predict that the issue of “incompetent crew” cannot be solved in a short time. To effectively prevent waterborne transportation accidents in China, according to Figure 10, paying attention to S1 (poor management on board the ships) and S2 (poor risk awareness of the captain during daily on-board management) may be a feasible way in the short term. For instance, improving the captain’s capacity would largely facilitate the elimination of S1 and S2.

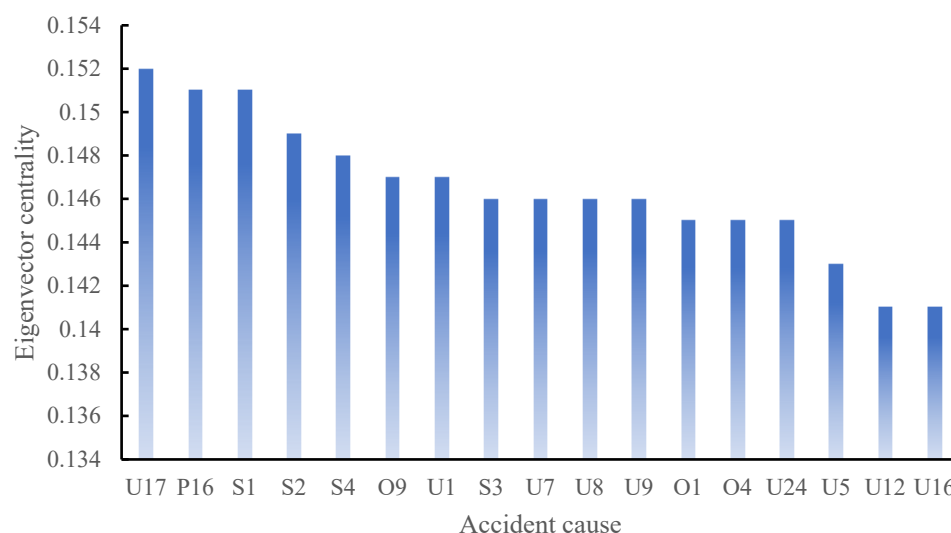


Figure 10. Top accident causes in terms of eigenvector centrality.

5.4. Activeness Analysis

According to Table 2 in Section 3.4, the activeness analysis for the nodes within the developed social network can be conducted by betweenness centrality, structural holes, and clustering coefficient, and the results are presented in Figure 11, Figure 12, and Figure 13, respectively. Notably, the analysis focus of these three parameters is different from each other.

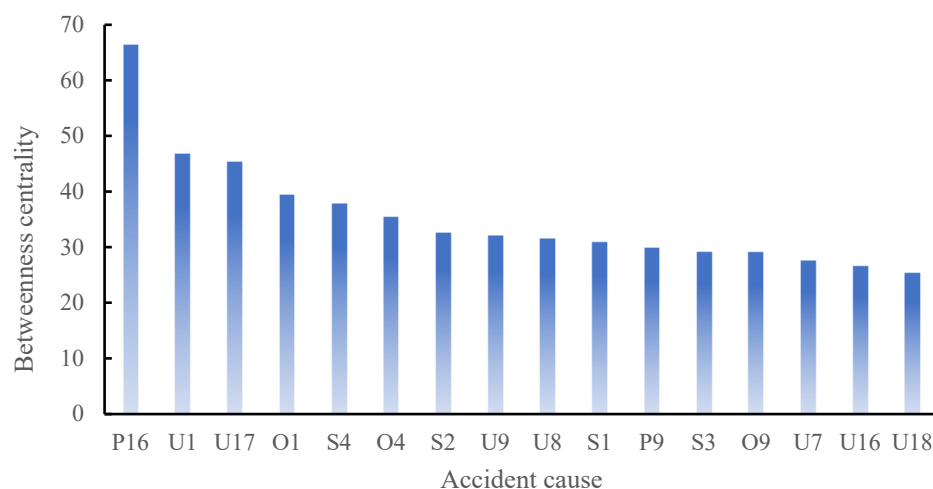


Figure 11. Top accident causes in terms of betweenness centrality.

The results of betweenness centrality are presented in Figure 11. Betweenness centrality measures the degree to which a node acts as a “bridge” based on global shortest paths in the network, reflecting its mediating role in connecting different co-occurrence clusters of contributing factors. Obviously, P16 (incompetent crew) has the highest betweenness centrality value, indicating that crew-related factors play a prominent bridging role in the co-occurrence network of accident causes. This aligns with the consensus in existing studies that crew-related factors are core components of waterborne transportation accident causes [44]. In actual accident scenarios, the co-occurrence results show that incompetent crew frequently co-occurs with multiple types of operational contributing factors. In addition, according to Figure 11, U1 (the crew on duty fails to maintain proper lookout) and U17 (failure to identify risks in a timely manner and take effective measures) also show strong mediating connectivity in the network. Overall, accident causes from the

external influence category do not rank high in betweenness centrality. Among the top 20% of contributing factors by betweenness centrality, 43.75% belong to the category of unsafe behaviors and states of on-board crew, and 25% fall into the unsafe supervision and management category (S4, S2, S1, S3).

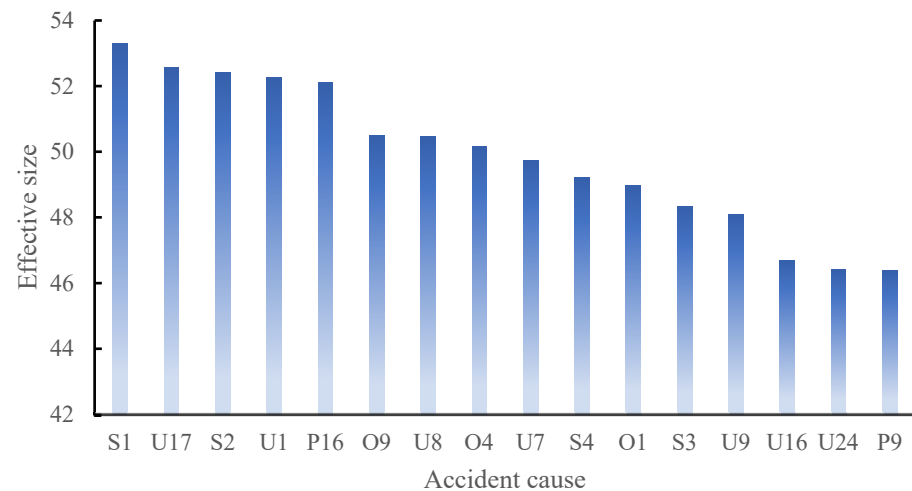


Figure 12. Top accident causes in terms of structural hole analysis.

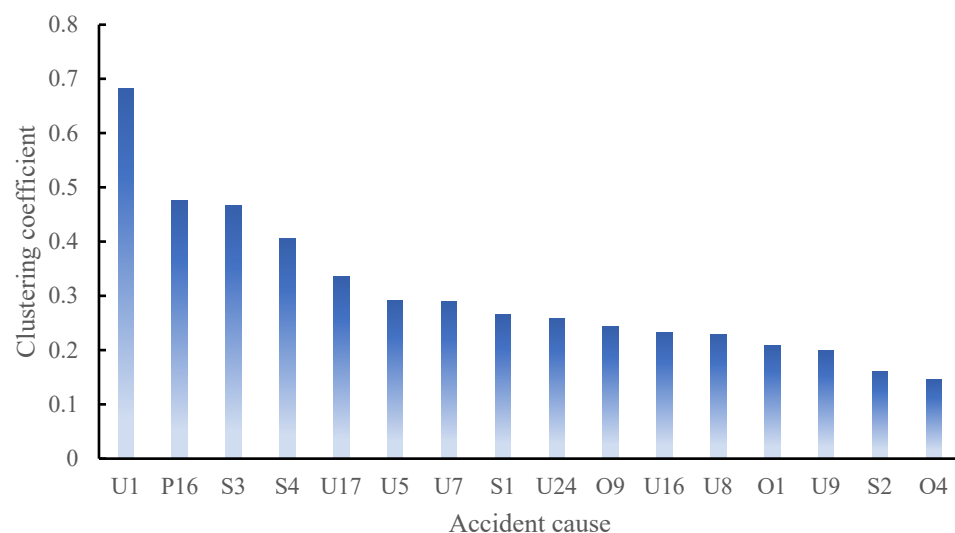


Figure 13. Top accident causes in terms of clustering coefficient.

Different from betweenness centrality, which measures whether a node acts as a “global bridge” linking different clusters of contributing factors, structural hole analysis focuses on the redundancy of a node’s connections. Simply put, nodes with high structural hole values connect to more distinct groups of contributing factors with little overlap in their connections, reflecting their unique role as connection hubs in the network. As discussed in Section 3.4, in this study, effective size is used to evaluate the structural hole of the nodes, and the results are presented in Figure 12. Notably, both S1 (poor management on board the ships) and S2 (poor risk awareness of the captain during daily on-board management) have high effective size values. Both contributing factors are directly associated with the management capacity of on-board captains, which corresponds to the connecting role of captains between on-board crew and shipping companies in the actual waterborne transportation system. This also indicates that optimizing captains’ management capacity can be taken as a key priority direction for on-board safety management, targeting core hub nodes in the co-occurrence network. Another node with prominent structural hole

attributes is U17 (failure to timely identify risks and take effective measures), according to Figure 12. Targeted management of such nodes faces certain practical difficulties, which are related to the wide co-occurrence coverage of incompetent crew (P16), a factor identified as relatively difficult to optimize in Section 5.2. In addition, U1 (the crew on duty fails to maintain proper lookout) also shows prominent structural hole characteristics: it maintains connections with diverse types of contributing factors, with very little overlap among these associated factors.

According to the definition of the clustering coefficient introduced in Section 3.4, the clustering coefficient is used to measure the local co-occurrence aggregation degree of nodes, reflecting how closely the neighboring contributing factors of a node are associated with each other. Figure 13 shows accident causes with high clustering coefficient values. Among the top 20% of contributing factors ranked by clustering coefficient, 50% belong to the category of unsafe behaviors and states of on-board crew, 25% fall into the unsafe supervision and management category, and only one factor (P16) from the preconditions for unsafe behaviors category is included. According to Figure 13, U1 (the crew on duty fails to maintain proper lookout) has the highest clustering coefficient, indicating that its neighboring contributing factors have the closest co-occurrence relationship and often appear simultaneously in accidents. In addition, P16 (incompetent crew) ranks second, with prominent local co-occurrence aggregation characteristics. Furthermore, “The operation of the ship is illegal due to invalid certificates” (S3) and “The shipping companies fail to provide sufficient and competent crew on board” (S4) also have relatively high clustering coefficients. These factors with high local aggregation can be taken as priority reference directions for shipping companies to carry out targeted safety management.

Overall, the multi-dimensional network structure analysis consistently shows that contributing factors from the external influence category rank low in all indicators, and the co-occurrence associations are dominated by internal factors, including crew unsafe behaviors and states, preconditions for unsafe behaviors, unsafe supervision and management, and organizational influence. The whole contributing factor co-occurrence network presents an internal-factor-dominated closed-like structural feature. It should be noted that this structural conclusion is obtained based on the sample dataset of this study, and its generalizability needs to be verified with more samples from different regions.

6. Conclusions

This study collects 886 waterborne traffic accident investigation reports released by China MSA (2013–2023) as its research database. The dataset is adopted to analyze the co-occurrence patterns and interactive relationships of accident contributory factors, and the obtained findings are expected to advance the safety management of China’s waterborne transportation. For this purpose, the section of accident cause analysis in the accident investigation report is first separated to develop the accident causation text database, and then, an HFACS-based hybrid deductive–inductive coding method combined with grounded theory coding procedures is applied with the assistance of software NVIVO 14 to identify, conceptualize, and categorize various accident causes in the accident investigation reports. As a result, all the accident causes are classified into 76 categories under a five-dimensional classification system. Considering the original data structure (the number of investigation reports varies for different accident types), the association rule analysis is applied to investigate the potential association rules involved in the accident causes for these seven accident types individually. Then, the social network analysis is applied to investigate the potential interaction patterns among these 76 categories, which is conducted by means of connection strength analysis, criticality analysis, and activeness analysis. The main conclusions are obtained as follows.

- (1) The strong association rules vary for the different accident types; generally, the strong association rules involved in the grounding (no rock) accidents are more noticeable compared with other kinds of accidents. In addition, the number of strong association rules involved in collision accidents is obviously more than in other accident types, and the self-foundering accidents are ranked second, which implies these two accident types are the most difficult to prevent.
- (2) Comprehensively considering the results of connection strength, criticality, and active-ness analyses, U17 (failure to identify risks timely and take effective measures) and P16 (incompetent crew) are identified as the two most important nodes to be addressed, with differentiated governance strategies based on their network characteristics. U17, whose structural importance resonates with the situation awareness deficits highlighted in prior collision studies [50], is linked to the watchkeeping and situational awareness requirements of Section A-VIII/2 of the STCW Code [51]. The current findings further designate it as a short-term governance priority, which allows for rapid improvement through operational optimization. Accordingly, shipping companies could consider implementing scenario-based risk identification checklists and targeted emergency drills to enhance crews' ability to detect and respond to risks promptly.
P16, whose central position aligns with the finding of Ma et al. [14] that crew incompetency is the most frequent precondition factor across accident types, corresponds to the competency and manning requirements of STCW Regulation I/2 [51] and ISM Code Chapter 6 [31]. Given its deep structural embedding in the association network, P16 is suggested as a long-term priority that likely requires sustained intervention. Measures such as improving crew competency assessment systems, strengthening continuous training, and ensuring adequate manning may help address its frequent co-occurrence with other contributing factors.
- (3) Within the network of accident contributing factors, nodes with high clustering coefficients are characterized by prominent local co-occurrence aggregation effects, making them potentially important foci for targeted management. These include U1 (the crew on duty fails to maintain proper lookout), S3 (the operation of the ship is illegal due to invalid certificates) and S4 (the shipping companies fail to provide sufficient and competent crew on board).
U1, whose high frequency across accident types confirms and extends earlier single-scenario findings on lookout negligence [52], corresponds to the lookout requirements stipulated in Section A-VIII/2 of the STCW Code and COLREGs Rule 5 [53]. Targeted measures such as strengthening watchkeeping discipline and inspections and scenario-based lookout training could be adopted to reduce its frequent co-occurrence with other risk factors.
S3, a compliance-related factor that warrants particular attention for waterborne transportation safety management in China, falls under the regulatory scope of the vessel certification and compliance requirements of SOLAS Chapter I [54]. Regulatory authorities might reinforce port state control inspections targeting certificate validity to address its clustering effects.
S4, characterized by strong clustering effects with supervision and precondition-level nodes in the network, corresponds to the manning and competency requirements specified in paragraph 6.2 of Chapter 6 of the ISM Code [31]. Shipping companies should ensure strict adherence to crew allocation standards to guarantee adequate and qualified manning, which could help break these local risk clusters.

However, there are still some limitations in this study in terms of data sources and analytical methods, and more in-depth and optimized research is needed in the follow-up work.

- (1) **Data limitations:** Constrained by the attributes of publicly available official reports, the dataset may carry inherent biases including underreporting, uneven quality, and inconsistent investigation focus. Samples are limited to Chinese waterborne transportation accidents with unbalanced accident type distribution, which may lead the identified co-occurrence patterns to be partially biased towards high-frequency accident types. In follow-up studies, multi-source accident data can be integrated to improve sample comprehensiveness and temporal coverage.
- (2) **Methodological limitations:** First, in terms of coding reliability, formal independent double coding by two independent coders was not implemented for the full sample in this study, and accordingly, no quantitative intercoder reliability coefficient is reported. Instead, a standardized coding rulebook, expert consensus validation, and theoretical saturation testing were adopted as alternative quality control measures to reduce coding ambiguity and mitigate subjective deviation. Nevertheless, these measures cannot fully substitute for formal intercoder reliability assessment. Potential residual subjectivity stemming from single-coder primary coding cannot be completely quantified or ruled out, which constitutes a clear methodological limitation of the qualitative coding procedure. Future research with sufficient resources can adopt independent double coding and report standardized intercoder reliability coefficients to further improve coding rigor and replicability. In addition, the thresholds of association rule mining are scenario-dependent and manually set, though core findings have been validated via robustness checks. Furthermore, both association rule analysis and the undirected co-occurrence network only capture statistical associations between factors and cannot infer causal directions—this is an inherent limitation of report-based co-occurrence analysis, as official reports do not specify strict temporal or causal sequences. Future research can improve coding rigor and introduce causal inference methods (e.g., combining Bayesian network analysis with social network methods) to further optimize the analytical framework.
- (3) **Conclusion and generalizability limitations:** The internal-dominated closed-like network feature is only applicable to the dataset of this study and cannot be directly generalized. The absence of external factors from top rankings across all network analytical dimensions may be attributed to these potential reasons: lower reporting frequency and underrepresentation of external contributing factors in official investigation reports, coding classification decisions, and the characteristics of the selected network metrics. This sample-level observation does not mean that external factors are unimportant for waterborne transportation accidents. In addition, the conclusions are mainly adapted to the Chinese maritime regulatory context, and caution is needed for cross-regional promotion. Future studies can supplement cross-regional samples for verification to enhance the generalizability of the conclusions.

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