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From text to network: A framework for identifying causal factors and risk propagation paths in maritime accidents

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ABSTRACT

To systematically investigate the complex causal mechanisms of maritime accidents, this study proposes an automated analytical framework that integrates Natural Language Processing (NLP) with complex network theory. The framework is designed to transform unstructured accident investigation reports into a quantifiable causal network that reflects systemic risk. Drawing on 564 official reports, this study constructs a standardised dataset of causal factors through a two-stage process combining automated preprocessing and manual coding. NLP techniques are then employed to extract causal relationships from the texts, enabling the construction of a weighted, directed complex network from discrete factors. To ensure the reliability of the framework, the extracted causal logic is verified by a domain expert panel, and the identified risk propagation patterns are validated against representative empirical cases. Topological analysis reveals that the causal network exhibits the “small-world” and “scale-free” properties characteristic of complex systems, indicating a high potential for efficient risk propagation mediated by a few key hubs. A multi-dimensional centrality assessment identifies static risk sources of high influence, including “Inadequate Supervision”, “Vessel Stability/Stowage Issues”, and “Adverse Weather/Sea State”. Furthermore, a risk pathway identification algorithm is applied to extract five typical risk propagation patterns. These pathways dynamically illustrate the systemic process by which risk evolves from latent managerial failures, through technical vulnerabilities and the actions of front-line personnel, to a major accident when triggered by specific environmental conditions. This work provides a dynamic, systematic network perspective for accident causation analysis, and its findings offer more precise intervention targets and process-based preventive strategies for maritime safety management.

1. Introduction

Amid accelerating global economic integration and sustained growth in international trade, the strategic imperative of maritime transport as the lifeline of the global supply chain has become increasingly evident [1,2]. However, escalating traffic density, complex navigational environments, and persistent human and technological uncertainties render maritime accidents a critical challenge, posing substantial threats to life and property while inflicting significant economic losses and environmental damage [3,4]. According to statistical data from the European Maritime Safety Agency (EMSA), 23,933 marine accidents were recorded in European waters between 2014 and 2023 [5]. As illustrated in Fig. 1, human error was implicated in 58.4% of these incidents. This finding highlights a pivotal challenge: dissecting the complex interplay among human, technological, and managerial factors has emerged as a central priority within the maritime safety domain. Consequently, the scientific analysis of accident causation, the identification of key risk factors, and the elucidation of risk evolutionary and propagation mechanisms hold paramount theoretical value and practical significance. Such analyses are essential for formulating effective safety strategies and preventing accidents [6–8]. Furthermore, ensuring the safety of maritime transportation systems necessitates an approach extending

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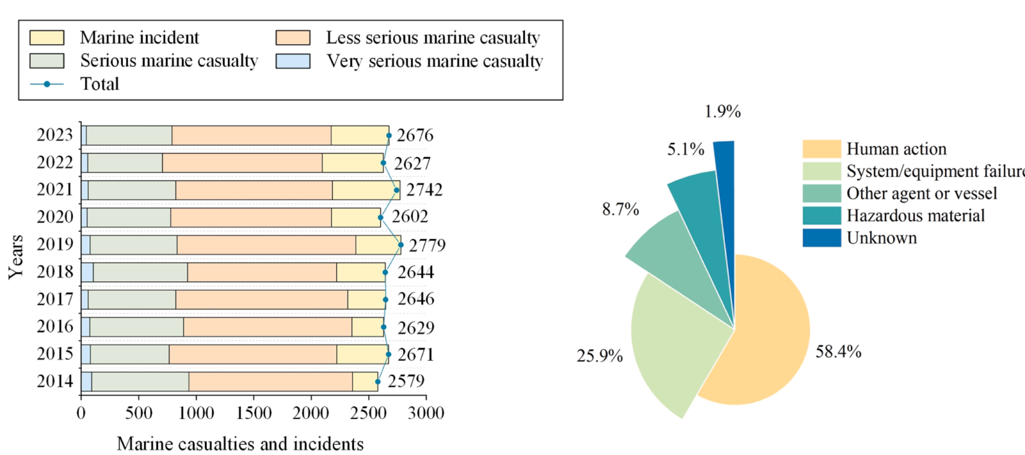
beyond static risk prevention to incorporate system resilience—the capacity to prepare for, absorb, respond to, and adapt to unexpected perturbations [9]. Accidents are frequently not isolated events but rather systemic chain reactions, often characterised as domino effects, where an initial trigger precipitates a cascade of catastrophic consequences [10,11]. Therefore, a deep understanding of these dynamic mechanisms is indispensable for developing robust safety interventions.

To enhance maritime traffic safety, the investigation into accident causation is approached from multiple dimensions, resulting in the formation of three primary research streams. The first of these focuses on the macroscopic statistical analysis of historical data, a conventional method for risk identification and assessment. This approach typically utilises officially published, structured accident data. Through the integration of methods such as Geographic Information Systems (GIS) and Kernel Density Estimation (KDE), high-risk areas are identified within the spatial dimension [12–15]. Regarding the temporal dimension, time-series analysis is employed to uncover periodic and trend-based patterns in accident occurrences [16,17]. While such methodologies prove effective for monitoring macroscopic risk trends and providing decision-making support for regional safety authorities, they are constrained by inherently coarse analytical granularity. By treating accidents as discrete and independent statistical events, such methods possess limited capacity to investigate internal accident dynamics, as they frequently overlook temporal correlation characteristics between incidents. Consequently, elucidating the intricate interplay among numerous causal factors or the micro-level evolutionary mechanisms through which risk propagates from initial triggers to the final accident remains challenging.

To investigate the intrinsic causal mechanisms underlying accidents, a second research stream centred on causal mechanism modelling emerges. Within this domain, models such as Fault Tree Analysis (FTA) [18,19], Event Tree Analysis (ETA) [20,21], and Bayesian Networks (BN) [22–25] are widely applied. These models effectively construct linear logical chains or probabilistic dependency relationships, providing robust tools for quantifying specific risk pathways. A significant advancement involves the integration of complex network theory, which reveals non-linear, networked correlations among systemic factors, thereby offering a promising perspective for understanding the systemic evolution of risk [26,27]. For instance, Fu et al. [9] develop a data-driven framework for risk and resilience analysis, emphasising the investigation of domino effects in maritime accidents where risk propagates through interconnected pathways. This underscores that identifying propagation paths from a systemic perspective is crucial for enhancing system resilience. Although theoretically advanced, these causal modelling methods encounter a shared bottleneck. Traditional models often prove inadequate for addressing dynamic coupling relationships among multiple factors in complex systems and typically necessitate pre-defined logical relationships, potentially introducing subjective bias. Conversely, the construction of complex network models relies heavily on high-quality, structured data inputs. In practice, however, detailed causal knowledge is frequently embedded within unstructured text, a constraint that significantly limits the application depth of these models when addressing real-world complexity.

To transcend the limitations of structured data, a third research approach emerges, centred on data-driven analysis with Natural Language Processing (NLP) at its core. With the advancement of deep learning technologies, research increasingly shifts towards utilising methods such as text mining to automatically extract knowledge from vast collections of unstructured accident investigation reports [28,29]. Advanced technologies, such as pre-trained language models, capture complex contextual semantics, significantly enhancing the efficiency and objectivity of information extraction. However, a primary limitation of current research in this domain is that it often remains restricted to the identification and extraction of discrete knowledge points, such as isolated accident causes or hazards. Furthermore, a mature and universally applicable framework for systematically and automatically integrating this fragmented knowledge remains largely absent. Such a framework is essential for constructing a quantitative risk network capable of reflecting global relationships and suitable for in-depth topological analysis. This constitutes a critical methodological gap between knowledge extraction and systemic risk modelling.

In summary, recent studies contribute significantly to the understanding of maritime accident causation. For instance, Li et al. [7] construct a data-driven risk model using a tree-augmented BN, which automatically learns the complex interdependencies between risk factors from historical accident records to predict collision probabilities. Liu et al. [30] apply complex network theory to model disruption propagation paths, revealing that accident evolution is not random but governed by quantifiable cascading effects through system resilience capabilities. Furthermore, Bairami-Khankandi et al. [31] combine systems-theoretic analysis with association rule mining to identify co-occurring risk patterns from investigation reports. However, such association-based methods primarily capture static correlations between factors rather than the directed, sequential logic of accident evolution. Similarly, Cao et al. [32] integrate association rule mining with complex network theory to analyse the topological structure and robustness of risk factor networks derived from accident records. Despite the individual merits of these approaches, significant research gaps persist. First, traditional statistical approaches often prove insufficient for capturing the complex, non-linear interactions inherent in maritime



(a) Annual trend of marine casualties and incidents (2014-2023)

(b) Distribution of marine accident causes

Fig. 1. Statistical overview of maritime safety in Europe: accident numbers and causal factors.

accidents. Second, although complex network theory is applied, most studies rely on structured checklist data, thereby sacrificing the rich semantic detail contained in textual investigation reports. Third, and crucially, existing network models typically offer a static topological view, often failing to trace the dynamic, sequential evolution of risk from latent failures to active errors. Consequently, a critical need exists for an integrated framework that automatically extracts granular causal knowledge from unstructured text and reconstructs the dynamic propagation mechanisms of accident causation.

Based on the identified challenges, this paper presents several key contributions.

1) It develops an end-to-end analytical framework that automatically extracts causal factor knowledge from unstructured maritime accident reports to construct a quantitative, global risk network spanning multiple accident types. In contrast to traditional methods reliant on manual analysis and pre-defined classifications, this automated framework significantly enhances the efficiency and objectivity of processing large-scale textual data.
2) It proposes a comprehensive importance assessment method based on multi-dimensional centrality metrics. By quantitatively analysing the network's topological structure, this method systematically identifies and ranks key causal factors, quantifying their local influence and global intermediary roles to provide precise targets for risk control.
3) It designs and applies a risk path identification algorithm to uncover dominant risk propagation patterns within the complex network. Surpassing conventional static factor importance rankings, this algorithm reveals the typical evolutionary trajectories of risk from initial triggers to final accidents from a dynamic perspective, providing a scientific basis for formulating targeted, process-based prevention strategies.

The remainder of the paper is organised as follows: Section 2 presents the literature review, summarising the primary research approaches in maritime accident causation analysis. Section 3 introduces the proposed methodological framework in detail, which consists of four main components: a two-stage process for causal factor extraction and coding from unstructured reports; the construction of a weighted, directed complex network based on causal relationships; a quantitative method for identifying key causal factors; and an algorithm for identifying key risk propagation paths. Section 4 provides the experimental analysis of the framework, while Section 5 discusses the findings and their implications. Finally, conclusions are highlighted in Section 6.

2. Literature review

2.1. Macro-level approach to risk identification and assessment

Macro-statistical analysis constitutes a fundamental technical approach in maritime risk research, typically relying on officially published, structured historical accident data. Such data, comprising key elements including accident frequency, time, geographical location, and vessel type, facilitate the effective identification of high-incidence areas and macro-level evolutionary trends through descriptive statistics and spatio-temporal analysis [33]. In the spatial dimension, Geographic Information Systems (GIS) technology is frequently combined with methods such as Kernel Density Estimation (KDE) to visualise accident distributions, thereby revealing the clustering characteristics of geographical risks. Zhang et al. [12] utilise KDE on GISIS maritime accident data from 2003 to 2018 to identify accident hotspots. This method is supplemented by K-means clustering for geographical partitioning, enabling the characterisation and comparison of accident patterns across different regions. Similarly, Wang et al. [14] introduce accident severity as an analytical weight. By integrating point density analysis and hotspot clustering techniques, relative accident density is calculated from GISIS data spanning 2010–2019, leading to the identification of high-frequency and high-risk zones. Regarding the temporal dimension, time-series analysis is widely applied to reveal cyclical and trend-based patterns of accident occurrences. Sui et al. [26] employ complex network mapping to study maritime accidents in the Yangtze River from 2011 to 2020, demonstrating that accident occurrences exhibit scale-free and "small-world" properties. This suggests that such events are not random but follow the principles of complex systems. To characterise annual trends, Zhou et al. [17] partition global maritime casualty data (2017–2021) into five annual subsets and construct BN models for each subset to analyse the dynamics of casualty characteristics and the influence of risk factors. Furthermore, Li et al. [16] conduct a systematic comparison of BN models constructed for two distinct periods, 2012–2017 and 2017–2021, which reveals the dynamic evolution and trends of the global maritime accident risk landscape over the past decade.

In summary, while such analyses based on macro-statistics are demonstrably effective for monitoring overall safety situations and identifying risk hotspots, their analytical granularity is typically coarse. Essentially, these studies focus on the presentation of macroscopic risk phenomena, making it difficult to delve into the complex causal relationships underlying the accidents or to elucidate the micro-level mechanisms of how risk evolves from initial triggers to the final event.

2.2. Modelling and analysis of accident causal mechanisms

To investigate the complex causal relationships underlying accidents, various modelling methods are developed and applied. Traditional causal models, including FTA [18,19], ETA [20,21], and BN [22–25], find extensive application within safety science. These models effectively structure logical accident chains and perform probabilistic inference, facilitating the identification of potential failure pathways and the quantitative assessment of accident progression. However, conventional application relies heavily on predefined event logic and expert knowledge, imposing limitations when analysing complex systems characterised by non-linear and dynamically coupled features [34]. The maritime transport system constitutes an inherently complex and dynamic domain with chaotic characteristics, where intrinsic operational principles prove difficult to delineate fully using traditional analytical methods [30]. Consequently, accidents frequently deviate from established linear or predeterminable causal paths and manifest as emergent phenomena arising from the dynamic evolution of the complex system. Therefore, for complex systems difficult to deconstruct into independent causal chains, an analytical framework capable of interpreting risk from a holistic and relational perspective is required.

Against this backdrop, complex network theory provides a novel modelling approach for the study of accident mechanisms. This method avoids reliance on predefined causal chains and reveals accident mechanisms through the topological structures and dynamic features of inter-element relationships within a system [35]. Deng et al. [36] extract accident chains from 123 major maritime accidents in coastal China to construct a complex network model comprising 96 risk factor nodes. This model is utilised to analyse the overall structural characteristics and evolutionary patterns of the accident risk network. Ma et al. [27] focus on human factors by analysing 104 ship grounding reports. The association strength of human factors between hierarchical levels of the Human Factors Analysis and Classification System (HFACS) framework is quantified using chi-square tests and odds ratio analysis. Based on these quantified associations, a directed weighted complex network is constructed to reveal the risk transmission mechanisms of human factors. Similarly, Cao et al. [32] develop a framework integrating association rule mining and complex network theory to conduct a comprehensive topological and robustness analysis of influential risk factors, offering a novel perspective on systemic vulnerability and risk propagation.

Overall, causal models and their extensions utilising complex networks are applied to elucidate accident mechanisms. However, the efficacy of these methods relies heavily upon high-quality, structured data inputs. Within the maritime safety domain, official accident investigation reports represent a valuable knowledge source yet exist predominantly as unstructured natural language text. Consequently, the objective and efficient extraction of structured, model-ready information from such texts constitutes a critical technical challenge that remains to be addressed.

2.3. Data-driven text knowledge extraction

To address the technical challenges of automatically extracting knowledge from unstructured accident reports, NLP and text mining methods are introduced into maritime safety research. Existing studies follow several technical paths. One approach, based on word frequency statistics and topic models, focuses on extracting core keywords and identifying latent accident themes and contextual patterns [37,38]. Another approach utilises pre-trained language models with Transformer architectures to capture complex contextual semantics, combined with sequence labelling techniques to extract key entities such as hazards and accident causes [39,40]. Following initial knowledge extraction, text vectorisation and clustering algorithms are employed to semantically merge and standardise the extracted entities, transforming unstructured text into structured knowledge units [41,42]. These knowledge units are utilised to construct higher-level analytical models, including ontology-based knowledge graphs for the systematic storage and querying of accident information [28,43], and accident evolution networks to characterise the associations and transmission mechanisms among risk factors [27,36].

Previous research advances methods for information extraction and knowledge structuring. However, these efforts primarily focus on the level of representation, involving the conversion of unstructured text into discrete knowledge points. Consequently, the systematic integration of these discrete points to automatically construct complex network models reflecting global causal relationships remains a challenge. Furthermore, conducting topological analysis on such networks to reveal risk propagation mechanisms warrants further investigation.

2.4. Research gaps

A review of maritime accident causation analysis reveals significant progress across key research areas, including macro-statistical analysis for identifying risk hotspots, causal mechanism modelling for understanding systemic risk, and data-driven text mining for extracting knowledge from unstructured reports. These advancements demonstrate a shift towards data-intensive and systemic approaches within safety science. However, an integrated framework capable of automatically transforming the rich and unstructured knowledge within accident reports into a comprehensive and quantifiable causation network for the systematic identification of key risk propagation paths remains absent. Existing research on maritime accident analysis is categorised based on primary focus as presented in Table 1. Despite these advancements, the critical gaps addressed in this study persist as follows.

(1) Lack of an end-to-end analytical framework that spans from raw text to systemic networks. Research streams such as macro-statistical analysis, causal modelling, and text information extraction have developed independently, with weak interconnections. Macro-statistical methods struggle to deeply characterise accident causation; causal models are constrained by the limited availability of structured data; and text extraction techniques lack a mechanism for systematic integration. Therefore, it is necessary to construct an automated framework that covers the entire process of data processing, knowledge extraction, and systemic analysis to achieve a direct mapping from unstructured accident reports to a quantitative risk network.

Table 1
Comparison of relevant maritime risk analysis studies.

Reference	Target region	Data type	Sample size	Method	Focus
Fu et al. [9]	Global; Arctic	Accident records	26; 419	Risk indices; Resilience analysis	Risk evolution & propagation; Systemic risk characteristics
Zhang et al. [12]	Global	Accident records	5726	GIS; KDE; K-means	Spatial pattern analysis
Wang et al. [14]	Global	Accident records	3484	GIS; Density analysis; Clustering	Spatial pattern analysis
Li et al. [16]	Global	Accident records	8097	BN	Risk evolution & propagation
Zhou et al. [17]	Global	Accident records	402	BN	Causal factor identification; Risk evolution & propagation
Jovanović et al. [19]	Europe	Accident reports	60	FTA; BN	Causal factor identification
Qiao et al. [20]	China	Accident reports	21	ETA; CN	Causal factor identification
Ma et al. [21]	China	Accident reports	34	ETA; CN	Risk evolution & propagation
Kamal and Çakır [22]	Istanbul strait	Accident records	418	BN	Causal factor identification
Wang et al. [23]	China	Accident reports	55	HFACS; BN	Causal factor identification; Risk evolution & propagation
Wang et al. [24]	China	Accident reports	220	BN	Causal factor identification; Risk evolution & propagation
Ma et al. [25]	China	Accident reports	318	HFACS; ARM; BN	Causal factor identification; Risk evolution & propagation
Sui et al. [26]	Yangtze river	Accident reports	3285	CN; Visibility graph algorithm	Risk evolution & propagation; Systemic risk characteristics
Ma et al. [27]	Global	Accident reports	104	HFACS; Grounded theory; CN	Causal factor identification; Risk evolution & propagation
Gan et al. [28]	China	Accident reports	241	Knowledge graph; Ontology, NLP	Causal factor identification; Risk evolution & propagation
Yan et al. [29]	China	Accident reports	207	NLP; BERT-CRF	Causal factor identification; Risk evolution & propagation
Liu et al. [30]	Arctic	Accident reports	57	CN; BN	Causal factor identification; Risk evolution & propagation; Systemic risk characteristics
Cao et al. [32]	UK; Canada	Accident reports	21; 206	ARM; CN	Causal Factor Identification; Risk evolution & propagation; Systemic risk characteristics
Deng et al. [36]	China	Accident reports	123	CN	Causal factor identification; Risk evolution & propagation; Systemic risk characteristics

CN: Complex network; ARM: association rule mining;.
BERT-CRF: Bidirectional encoder representations from the transformer - Conditional random fields.

(2) Inadequate multi-dimensional quantitative assessment of key causal factors. While existing research can identify key risk factors, it often relies on single metrics or qualitative judgements. The importance of a node in a complex network is multi-dimensional, encompassing aspects such as its direct influence, its control over risk propagation, and its efficiency in diffusing impact. A comprehensive assessment method that integrates multiple topological indicators is needed to accurately characterise the multifaceted roles of key factors within the risk network.
(3) Limited understanding of dynamic risk transmission pathways within the network. Analyses based on complex networks have largely focused on static structural features, primarily identifying important nodes, whereas accident evolution is inherently a dynamic process. Current methods seldom characterise the associative pathways between key nodes and their roles in typical accident evolution scenarios, lacking a systematic analysis of risk propagation chains.

To address these challenges, an automated analytical framework integrating NLP with complex network theory is proposed. The objective involves establishing a systematic process extending from knowledge extraction from accident texts to the modelling of risk networks. To clarify the methodological advancements of this approach, a comparative summary between the proposed framework and existing causal analysis methods is provided in Table 2.

Table 2
Methodological comparison of causal analysis approaches.

Method	Data & construction logic	Key advantages	Limitations
FTA / ETA	Constructs linear logical chains based on pre-defined event logic	Provides clear failure pathways and standardised logical deduction	Relies on subjective expert pre-definition; cannot model non-linear coupling
BN	Models probabilistic dependencies using directed acyclic graphs	Handles uncertainty well through probabilistic reasoning and quantitative assessment	Highly dependent on high-quality structured data; relies on static logic assumptions
Traditional complex networks (manual construction)	Constructs network topology through manual extraction from reports	Reveals global systemic interactions and identifies key hub nodes	Focuses on static structural features; labor-intensive and inefficient for large datasets
Word frequency / topic models	Analyses keyword frequency and statistical co-occurrence in texts	Automatically discovers macroscopic themes; efficient for large-scale corpus	Inherently coarse granularity; ignores semantic context and lacks causal logic
Deep learning models	Mines entities and relations based on deep semantic context extraction	Captures complex semantics with high precision and context awareness	Extracts fragmented discrete knowledge points; lacks systemic network integration
Proposed method	Automatically integrates NLP-mined causal chains into a systemic network.	Identifies dynamic risk propagation paths; objective and fully data-driven	Granularity is constrained by the narrative detail of the original investigation reports

3. The proposed methodology

To systematically uncover the complex causal mechanisms underlying maritime accidents, this study establishes a comprehensive, data-driven analytical framework that integrates NLP with complex network theory. The overarching objective is to transform large volumes of unstructured accident reports into a quantifiable network model reflecting systemic risks. As illustrated in Fig. 2, the framework is structured into four logically interconnected sections.

First, Section 3.1 details the data standardisation phase, employing a two-stage hybrid method that combines automated preprocessing with expert coding to convert raw narrative texts into a standardised, high-quality dataset of causal factors. Subsequently, Section 3.2 introduces the network construction methodology, where NLP techniques are utilised to mine dynamic causal logic and temporal relationships from the text, assembling discrete factors into a weighted, directed complex network. Building on this topology, Section 3.3 presents the quantitative assessment methods by applying multi-dimensional topological metrics to identify and rank key static risk factors based on their structural importance within the system. Finally, Section 3.4 proposes a novel algorithm for risk pathway identification, moving beyond static analysis to uncover dynamic risk propagation patterns and reveal typical accident evolution trajectories. These components constitute a coherent research pipeline, progressing from raw data processing to systemic network modelling, and culminating in the identification of dynamic risk mechanisms.

3.1. Safety accident causal factor identification and analysis

3.1.1. Data acquisition and preprocessing

The empirical basis for this research is derived from a systematic collection of 564 official maritime accident investigation reports. This dataset spans the period from 2019 to 2023 and is sourced directly from the publicly available database of the China Maritime Safety Administration (MSA). To ensure the quality and depth of textual data for NLP analysis, strict selection criteria are applied. The dataset consists solely of official investigation reports released by maritime authorities to ensure factual reliability. Furthermore, selection focuses exclusively on full-text reports containing detailed narratives of the accident process and causal analysis, thereby excluding brief statistical summaries or preliminary notices. Additionally, a comprehensive collection of all available full reports from the past five years is incorporated to reflect recent safety trends. While this selection strategy ensures the richness of causal information required for complex network modelling, it inherently concentrates on incidents significant enough to warrant full investigation. Consequently, the depth of causal complexity is prioritised over simple frequency statistics of minor incidents. Regarding language consistency, the dataset is restricted to official documents published in Simplified Chinese. Unlike unstructured social media text, these reports follow a semi-structured regulatory format, typically comprising distinct sections for factual information, causal analysis, and conclusions. This linguistic and structural uniformity is utilised to facilitate the targeted extraction of causal logic while minimising noise from administrative metadata.

To convert these raw PDF documents into a standardised dataset suitable for network modelling, a rigorous preprocessing pipeline is designed and implemented. Initially, PDF files are converted into plain text format. Information not directly pertinent to the core causal chain, such as specific dates and routine operational dialogues, is eliminated. Subsequently, the text is segmented into sentence units using Chinese punctuation delimiters to maintain semantic integrity. To address linguistic ambiguity, a domain-specific dictionary is constructed, wherein heterogeneous textual descriptions are mapped to standardised risk concepts based on expert knowledge.

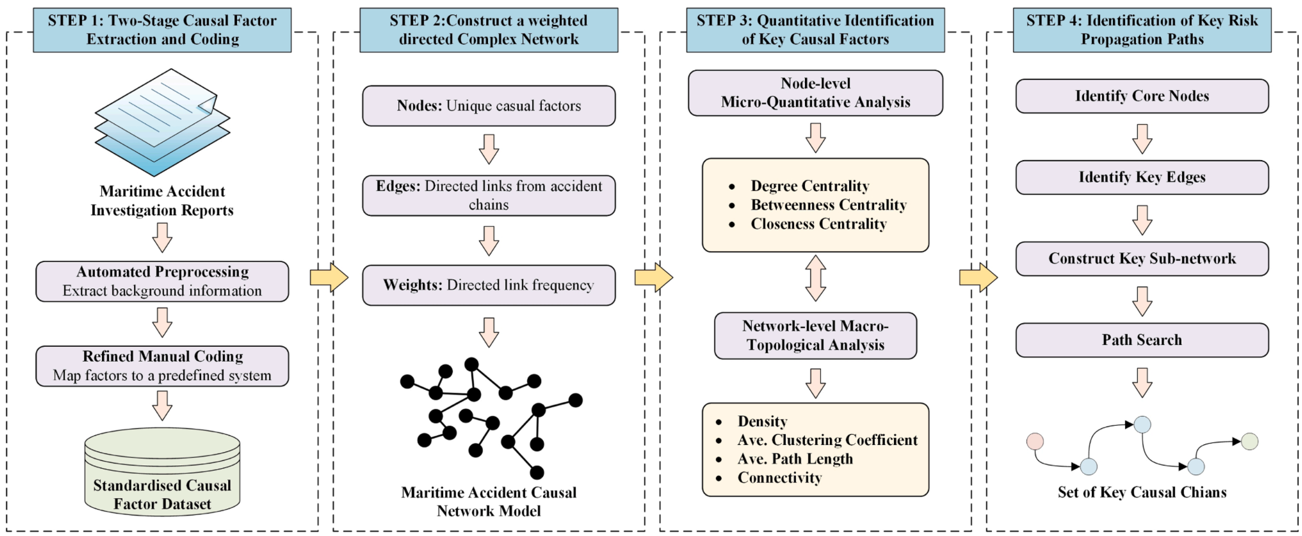


Fig. 2. Identification and analysis of maritime accident causal factors.

3.1.2. Automated keyword extraction based on TF-IDF

To efficiently process the large-scale corpus, the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm is employed as a pre-screening mechanism to identify candidate risk factors. Although TF-IDF focuses on term frequency and potentially overlooks semantic context compared to deep learning models such as Bidirectional Encoder Representations from Transformers (BERT), it is utilised distinctively for initial keyword discovery due to its high interpretability in constructing a controllable domain lexicon. Specifically, this function filters general administrative terms carrying low discriminatory power and highlights distinctive accident-related terms. Significantly, the extraction of complex causal logic relies not on TF-IDF but is reserved for the subsequent syntax-based analysis and expert verification detailed in Section 3.1.3, ensuring that identified relationships reflect genuine causality rather than frequency bias.

The methodology relies on two core assumptions. First, each accident report is treated as a collection of terms wherein grammar and word order are disregarded, and analysis focuses solely on term frequency [44]. Second, the importance of a term is considered directly proportional to frequency within a single document and inversely proportional to prevalence across the entire corpus [45]. Based on these assumptions, the algorithm evaluates the weight of each term by combining two core metrics. The first, Term Frequency (TF), quantifies the local importance of a term within a specific document. For a given term (t_i) in an accident report (d_j), the TF value is defined as the ratio of occurrences to the total number of terms in the document, a normalisation accounting for variations in document length. This relationship is expressed in Eq. (1).

$$TF_{i,j} = \frac{n_{i,j}}{\sum_{k=1}^{P} n_{k,j}} \tag{1}$$

where $n_{i,j}$ denotes the number of occurrences of term t_i in accident report d_j, and $\sum_{k=1}^{P} n_{k,j}$ is the sum of the occurrences of all P terms in report d_j.

The second metric, Inverse Document Frequency (IDF), measures the discriminatory power of a term across the entire corpus. Higher term frequency across documents results in a lower IDF value, effectively reducing the weight of common terms like “vessel” and “navigation” whilst increasing the importance of domain-specific terminology. The calculation is expressed in Eq. (2).

$$IDF_i = \log \frac{|D|}{|\{j : t_i \in d_j\}|} \tag{2}$$

where $|D|$ represents the total number of accident reports in the corpus, and $|\{j : t_i \in d_j\}|$ denotes the number of reports that contain the term t_i.

The TF-IDF value is subsequently calculated by multiplying these metrics, providing a composite measure of the importance of a term (t_i) to a specific report (d_j). A higher TF-IDF value indicates a greater likelihood that the term constitutes a core keyword for that report. The formula is expressed as Eq. (3).

$$TF - IDF_{i,j} = TF_{i,j} \times IDF_i \tag{3}$$

This algorithm facilitates the automated and objective identification of a representative list of keywords from the extensive text corpus. Furthermore, this quantitative extraction serves as a robust empirical foundation for subsequent expert-based qualitative analysis. The extracted keywords and associated sentences are subject to manual verification by domain experts to confirm causal logic and contextual accuracy. This step effectively compensates for the semantic limitations of the bag-of-words approach and ensures precise factor categorisation.

3.1.3. Key sentence identification and qualitative analysis

Given that isolated keywords are insufficient to convey complete causal logic, a context-aware sentence extraction algorithm is employed. Punctuation marks serve as delimiters to extract complete sentences containing high-value TF-IDF keywords from each report automatically. This automated process acts as a semantic filter that effectively strips away non-causal narratives such as administrative logs, vessel parameters, and routine weather reports unrelated to the incident. The result is a refined dataset of 2,810 candidate key sentences containing potential risk factors. This approach preserves the original context while significantly reducing the data volume requiring manual review.

Following extraction, the candidate sentences undergo rigorous qualitative analysis. To ensure the reliability of causal identification, a human-in-the-loop verification protocol is adopted. An expert panel comprising five members is established to review, validate, and rectify the algorithmically extracted candidates rather than reading the full texts. The panel composition is designed to bridge theoretical knowledge with operational reality. As detailed in Table 3, the group consists of three senior academics specialising in maritime safety and two active seafarers possessing extensive seagoing practice.

To minimise subjective bias and ensure coding consistency, a three-step procedure is implemented. First, a pilot coding session is conducted using 50 randomly selected samples to align expert understanding of factor definitions and coding rules. This calibration phase continues until the inter-coder agreement rate exceeded 90%.

Table 3
Profile of the expert panel for qualitative analysis.

No.	Current position	Education / Qualification	Professional experience	Research area
1	Professor	Ph.D. in communication and transportation engineering	22 years in academic research; Former chief officer	Risk assessment; Accident modelling; Human reliability analysis
2	Associate professor	Ph.D. in traffic information engineering & control	13 years in maritime research; Former third officer	Maritime traffic engineering; Intelligent navigation
3	Associate professor	Ph.D. in traffic information engineering & control	7 years in maritime safety management research	Safety management systems; Maritime policy; Data mining
4	Captain	Unlimited Master mariner	22 years sea-going experience (10 years as captain)	Ship handling; Emergency response; Bridge resource management
5	Chief officer	Unlimited chief mate	8 years sea-going experience (1 years as chief officer)	Cargo operations; Watchkeeping; Onboard safety procedures

Second, during the formal coding phase, all five experts independently review the complete set of 2,810 candidate sentences. Although this implies a comprehensive workload, the task is streamlined into a rapid validation and rectification process rather than extraction from scratch. Specifically, the experts refine the candidate dataset through deep semantic analysis to improve data quality beyond the capabilities of automated keywords. This process involves three specific cognitive tasks. First, experts perform contextual disambiguation to correct semantic misinterpretations where the algorithm flags high-frequency terms irrelevant to the accident cause, such as distinguishing between a routine check mentioned in background information and a failed check that led to the incident. Next, experts infer implicit causal relationships where the NLP algorithm fails to capture links due to missing connectives. For instance, narrative logic indicating causality without explicit conjunctions is manually identified and coded. Finally, experts perform logical decomposition for complex sentences involving multiple concurrent factors. This ensures that intertwined risks, such as fatigue leading to both operational error and violation, are accurately mapped as distinct edges in the network rather than a single ambiguous cluster.

Third, a consensus meeting is held to address discrepancies. Cases involving conflicting codes are reviewed collectively, and final classification is determined only when unanimous agreement is reached. To statistically validate consistency across the five-member panel, Fleiss' Kappa is calculated. The resulting coefficient of 0.86 indicates almost perfect agreement. This protocol ensures that the final dataset combines the efficiency of automated mining with the logical precision of human expertise.

3.1.4. Classification and coding system construction of causal factors

Following factor induction, a distinct classification and coding system is developed. Drawing upon established safety theories, the classification structure integrates the 4M framework for top-level categories and adapts HFACS to structure human-related subcategories. Consequently, all standardised causal factors are categorised initially into four primary groups comprising Human, Management, Technology, and Environment. Although hierarchical logic is adopted from these theoretical models, specific definitions for bottom-level factors are derived inductively from the accident report corpus. To delineate boundaries between the Technology and Ship categories, specific definitions based on the distinction between subsystem reliability and global vessel seaworthiness are established. The Technology category is defined strictly as the functional failure of active onboard subsystems including machinery and electronics. Conversely, the Ship category pertains to inherent naval architectural properties of the vessel itself, such as stability and manoeuvrability, which exist independently of specific equipment breakdowns. Accident types are similarly classified into categories including collision, grounding, fire and explosion, and foundering. Subsequently, each factor is assigned a unique, hierarchically structured code, culminating in a mapping system linking textual keywords to standardised descriptions. The detailed mapping system and

Table 4
Taxonomy for maritime accident causation and typology.

Main category	Sub-category	Causal factor	Factor code
Human	Cognitive	Judgement/Decision error	H-COG-01
		Negligence/Forgetfulness	H—COG-02
		Insufficient risk assessment	H-COG-03
		Information overload	H—COG-04
	Skill	Insufficient skill level	H-SKL-01
		Lack of knowledge	H-SKL-02
		Insufficient training/Drills	H-SKL-03
		Lack of experience	H-SKL-04
	State	Insufficient safety/Vigilance awareness	H-STA-01
		Physiological/Psychological fatigue	H-STA-02
		Adverse psychological state	H-STA-03
	Violation	Rule/Regulation violation	H-VIO-01
		Procedural violation	H-VIO-02
	Cooperation	Poor communication/ Coordination	H—COP-01
		Improper team/Resource management	H-COP-02
Technology	Hardware	Equipment/Hardware failure	T—HW-01
		Critical equipment failure	T-HW-02
		Improper/Insufficient maintenance	T-HW-03
		Equipment design flaw	T-HW-04
	Software	Software/Algorithm defect	T-SW-01
		Sensor/Information system failure	T-SW-02
		Network/Data security issue	T-SW-03
		Communication system failure	T-SW-04
Ship	Performance	Manoeuvrability/Hull issue	S-PRF-01
		Stability/Loading problem	S-PRF-02
		Insufficient Ice-breaking capability	S-PRF-03
Environment	Natural	Adverse weather/Sea conditions	E-NAT-01
		Poor visibility	E-NAT-02
		Ice-covered area impact	E-NAT-03
		Complex Hydrographic/ Waterway conditions	E-NAT-04
	Traffic	Complex traffic flow/Encounter situation	E-TRF-01
		VTS/Shore-based support issue	E-TRF-02
Management	Regulatory	Incomplete or unimplemented rules/Procedures	M-REG-01
		Insufficient emergency plan/ Response	M-REG-02
	Supervision	Inadequate supervision	M-SUP-01
		Improper resource/Manning management	M-SUP-02
Accident	Collision	Collision	A-COL
	Grounding/ Stranding	Grounding/Stranding	A-GRD
	Fire/Explosion	Fire/Explosion	A-FIR
	Capsizing/ Sinking	Capsizing/Sinking	A-CAP
	Others	Allision/Contact/Cargo	A-OTH

coding are presented in Table 4.

Through the explicit identification and standardisation of causal factors into a structured taxonomy, the foundational dataset for this phase is established. However, these factors exist primarily as discrete entities. To reveal systemic risk mechanisms, the reconstruction of dynamic interrelationships and logical dependencies among these factors is required. This objective is addressed in the subsequent network construction section.

3.2. Construction of the maritime accident causal network

To integrate discrete causal factors into a cohesive whole reflecting systemic risk, complex network theory is employed to construct a weighted directed maritime accident causation network, denoted as $G = (V, E, W)$. This method is selected based on the core understanding that maritime accidents are not triggered by single, isolated factors but emerge as outcomes of complex, non-linear interactions among multiple elements within the system. Consequently, the complex network model transcends traditional linear causal chain analysis by mapping and quantifying systemic interrelationships through topological structure.

In this network model, the set of nodes (V) all unique, standardised causal factors, wherein each node (v_i) represents a fundamental unit of the risk system. The set of edges (E) represents interactions between these causal factors. Through the application of NLP techniques, causal logic and temporal relationships embedded within accident report texts are mined. Directed edges (e_{ij}) between causal factors are constructed by extracting and integrating numerous accident chains. Therefore, a directed edge from factor v_i to v_j signifies a risk transmission path, precisely depicting the direction of risk propagation.

To reflect the varying strength of associations between different factors, each edge in the network is assigned a weight (W). The weight (w_{ij}) of an edge (e_{ij}) represents the strength or frequency of that particular risk transmission relationship. A higher weight indicates that the risk pathway constitutes a frequent and pervasive systemic feature in maritime accidents.

Through these procedures, fragmented knowledge contained within a large volume of unstructured text is transformed into a structured, quantifiable complex network that accurately portrays the risk evolution process. This provides a solid foundation for subsequent topological analysis and key risk identification.

To ensure that identified relationships and directionality reflect genuine causal logic rather than spurious co-occurrences or linear text order, a semantic dependency analysis strategy is employed. The determination of edges relies on explicit linguistic cues within accident reports rather than the mere sequence of words. For instance, causal connectives and syntactic structures are analysed to distinguish between forward causality and retrospective attribution. Furthermore, extracted causal pairs are reviewed by the expert panel to correct logical inversions and prune invalid associations, particularly in complex narratives involving passive voice or non-sequential descriptions. Specific examples of the mapping between linguistic patterns and directed edges are provided in Table 5.

To rigorously control data quality and eliminate potential false positives, a human-in-the-loop verification mechanism is implemented. Following automated extraction, all candidate causal pairs are reviewed by the expert panel to prune invalid associations and correct logical inversions. The reliability of this verification process is quantified using Fleiss' Kappa coefficient, yielding a value of 0.86. This high level of inter-coder agreement confirms that the filtering of false positives is conducted with statistical consistency, ensuring that final edges in the network reflect genuine, verified causal logic.

The construction of this verified network model provides a robust topological representation of the accident system. Based on this structure, the strategic importance of each node is quantitatively evaluated using specific mathematical metrics in the subsequent section.

Table 5
Examples of causal logic extraction and directionality validation.

Original sentence extract (Translated)	Linguistic cue	Source node (Cause)	Target node (Effect)	Direction logic
The officer was suffering from fatigue, which led to a negligence in lookout.	led to (Forward)	H-STA-02 (Fatigue)	H—COG-02 (Negligence)	Forward Causal
The collision occurred due to the steering gear failure.	led to (Forward)	T-HW-02 (Steering Failure)	A-COL (Collision)	Reverse Attribution
Heavy fog reduced visibility, causing the vessel to ground.	due to (Backward)	E-NAT-02 (Poor Visibility)	A-GRD (Grounding)	Forward Causal
The captain failed to verify the position after the GPS malfunctioned.	after (Temporal)	T-SW-02 (Sensor Failure)	H-COG-01 (Judgement Error)	Temporal Sequence

3.3. Network topology analysis and key factor quantification

To systematically uncover intrinsic structural risk properties and identify influential key factors within the constructed causation network, complex network analysis is utilised. The analytical framework integrates a macroscopic analysis of overall network structure and risk evolution efficiency using global topological metrics with a microscopic analysis quantifying node centrality to evaluate the strategic importance of individual causal factors.

3.3.1. Macro network topological characteristics

Macroscopic analysis quantifies the overall connectivity, clustering, and transmission efficiency of the accident causation network, establishing a basis for understanding accident system complexity. Initially, the number of Weakly Connected Components serves as an indicator wherein a higher value signifies greater network fragmentation and a larger number of independent causal subsystems within the network [46]. To further quantify the principal network structure, the Largest Component Ratio is utilised, with the calculation expressed in Eq. (4).

$$S = \frac{N_{max}}{N} \tag{4}$$

where S represents the Largest Component Ratio, N_{max} is the number of nodes in the largest connected component, and N denotes the total number of nodes in the network. A higher S value indicates a more cohesive network structure, suggesting that most causal factors are situated within a single, interconnected causal web.

Following the assessment of fundamental connectivity, network density is utilised to quantify the degree of nodal interconnection. This metric represents the ratio of existing edges to the total number of potential edges within the network. A high density value implies that causal factors exhibit extensive and complex interactions. The definition for this metric is presented in Eq. (5).

$$\rho = \frac{M}{N(N-1)} \tag{5}$$

where ρ denotes the network density, N represents the total number of nodes, and M is the total number of edges in the network.

Finally, to interpret transmission efficiency and structural patterns, small-world network properties are analysed. Key indicators include the average path length and the average clustering coefficient, calculated via Eqs. (6) and (7) respectively. The average path length is utilised to measure the average risk propagation distance within the network. A shorter average path length signifies higher risk transmission efficiency and, consequently, more rapid accident evolution.

$$L = \frac{1}{N(N-1)}\sum_{i\neq j} d(i,j) \tag{6}$$

where L represents the Average Path Length, N corresponds to the total number of nodes in the network, and $d(i,j)$ is the length of the shortest path between nodes i and j.

$$\overline{C} = \frac{1}{N}\sum_{i=1}^{N}\frac{2E_i}{k_i(k_i-1)} \tag{7}$$

where $\overline{C}$ is the Average Clustering Coefficient, N denotes the total number of nodes, k_i represents the degree of node i, and E_i corresponds to the number of edges between its neighbouring nodes.

3.3.2. Node centrality and key factor quantification

To quantify the critical role and influence of each causal factor within the accident evolution process, a microscopic-level evaluation of network nodes is conducted using various centrality metrics. First, Degree centrality provides the most direct measure of immediate nodal influence. In a directed network, this metric is disaggregated into out-degree and in-degree, representing the capacity to influence other factors and the susceptibility to the influence by others, respectively, as calculated in Eq. (8). Consequently, nodes with high out-degree are regarded as risk sources, while those with high in-degree represent risk convergence points.

$$k_i^{out} = \sum_{j=1}^{N} a_{ij},\ \ k_i^{in} = \sum_{j=1}^{N} a_{ji} \tag{8}$$

where a_{ij} is an element of the adjacency matrix, taking a value of 1 if an edge exists from node i to node j, and 0 otherwise.

Closeness centrality measures the centrality of a factor within the network, reflecting the average distance to all other nodes. A higher closeness centrality value indicates that the factor occupies a pivotal position, enabling rapid influence dissemination throughout the system. The calculation for this metric is presented in Eq. (9).

$$C_c(i) = \frac{N-1}{\sum_{j=1,j\neq i}^{N} d(j,i)} \tag{9}$$

where $C_c(i)$ represents the Closeness Centrality of node i.

Betweenness centrality assesses the importance of a factor as an intermediary within the network. This metric is determined by the number of shortest paths between all other pairs of factors passing through the specific node. A factor with a high betweenness centrality value therefore constitutes a critical control point for risk propagation across different network modules. The calculation follows Eq. (10).

$$C_b(i) = \sum_{h\neq i\neq j}\frac{\sigma_{hj}(i)}{\sigma_{hj}} \tag{10}$$

where $C_b(i)$ is the Betweenness Centrality of node i; σ_{hj} signifies the total count of shortest paths between nodes h and j; and $\sigma_{hj}(i)$ corresponds to the number of these shortest paths that traverse node i.

Finally, to establish a comprehensive metric for node importance, a composite indicator integrating six centrality metrics is developed. Given that these metrics exhibit distinct physical meanings and varying value ranges, a Min-Max normalisation process is applied to standardise all values into a dimensionless [0,1] interval, thereby eliminating heterogeneity and ensuring strict comparability. Subsequently, an equal-weighting strategy is adopted to compute the arithmetic mean of the normalised values. This approach is selected to mitigate subjective bias inherent in arbitrary weight assignment, particularly given the absence of consensus in current literature regarding the relative dominance of any single topological feature in maritime accident causation. By treating local influence, global closeness, and intermediary control capability equally, the composite index ensures a robust and balanced assessment.

While the centrality metrics discussed effectively identify static key nodes, an isolated assessment of individual factors proves insufficient to capture the sequential evolution of accidents. To address this limitation, a path-searching algorithm is introduced in the final methodology section to uncover the dynamic risk propagation chains connecting these nodes.

3.4. Identification of key risk propagation paths

While the preceding topological analysis identifies key factor nodes of static importance, an isolated assessment of individual factors fails to elucidate fully the underlying mechanisms of dynamic risk evolution within a complex system. The occurrence of a maritime accident constitutes not a simple aggregation of critical factors but typically follows specific propagation pathways composed of multiple factors arranged in a logical sequence. Consequently, a transition from static node importance analysis to dynamic pathway identification is essential for deepening the understanding of causality and enabling precise risk interventions. The objective of this section is to mine and identify the most critical and frequent risk propagation pathways from the complex causation network. These pathways illustrate typical patterns by which risk evolves from initial factors, through intermediate stages, to the final accident. The identification of these key causal chains holds theoretical and practical significance for understanding evolutionary patterns, interrupting risk propagation, and formulating comprehensive safety management strategies spanning from pre-emptive prevention to in-event intervention.

To fulfil this objective, a systematic identification procedure based on the selection of core network elements and a path-searching algorithm is designed. The procedure commences by defining Core Nodes and Key Edges, derived from the quantitative analysis in Section 3.3. Core Nodes represent causal factors with the highest composite importance rankings, forming the most influential set of nodes. Key Edges correspond to those with the highest weights, representing the most frequent and stable causal associations. Analysis subsequently focuses on the sub-network constituted by these core elements. Using a path-searching algorithm from graph theory, all simple paths between any two Core Nodes within a predefined length threshold are systematically explored. To ensure the identified pathways are physically meaningful and consistent with maritime accident theories, algorithmic parameters are determined based on theoretical frameworks and empirical testing. Specifically, the maximum path length is set according to established benchmarks [47]. This constraint aligns with the Swiss Cheese Model of accident causation, where risk evolution typically involves a finite sequence of defensive layer failures—ranging from latent management defects to active operational errors—rather than an indefinite chain. A path length that is too short fails to capture the cross-level propagation mechanism, while excessive length introduces irrelevant noise. Similarly, the threshold for Key Edges is established based on the network weight distribution to filter out low-frequency, coincidental associations. This strategy retains only robust causal links constituting the network backbone, thereby ensuring the representativeness of extracted chains. Finally, all candidate causal chains passing this filter are ranked in descending order based on cumulative path weight. A higher cumulative weight signifies that the risk propagation pattern represented by the chain is more frequent in historical accident data and thus embodies a stronger systemic risk. This methodology enables the identification of statistically significant and practically relevant key risk propagation pathways from the complex network structure, providing a dynamic entry point for understanding and intervening in the accident evolution process. The algorithm for identifying these pathways is outlined in Table 6.

Regarding computational complexity, the algorithm's efficiency is

Table 6
Key risk propagation paths identification algorithm.

Algorithm
Input: $G = (V, E, W)$, $V_{core} \subseteq V$, $E_{key} \subseteq E$, L_{max}
▷/* $G = (V, E, W)$ indicates a weighted directed graph, where V is the set of nodes, E is the set of edges, and W is the set of weights. V_{core} is a set of core nodes identified by centrality analysis. E_{key} represents a set of key edges identified by high weights. L_{max} denotes the maximum allowed length for path. */
Output: P_{ranked}
▷/* P_{ranked} is a ranked list of key casual chains. */
$P_{candidate}$ = [] // Initialise an empty list for candidate chains //
for each pair of distinct nodes (v_{start}, v_{end}) **in** V_{core} **do**
find all simple paths **from** n_{start} **to** n_{end} with length $\leq L_{max}$:
$Paths_{found} = AllSimplePaths(G, n_{start}, L_{max})$
for each path **in** $Paths_{found}$ **do**
is_key_path = True
for i from 0 to length(path) – 2 **do**
$edge = (path[i], path[i+1])$
if $edge$ is **not** in E_{key} **then**
is_key_path = False
break
end if
end for
if is_key_path == True **and** length(path)>2 **then**
$W_{path} = \sum_{i=0}^{length(path)-2} W(path[i], path[i+1])$ // Calculate cumulative weight//
add {path, W_{path}} **to** $P_{candidate}$
end if
end for
end for
sort $P_{candidate}$ in descending order based on W_{path}
$P_{candidate}$ = the sorted list of paths from $P_{candidate}$
return P_{ranked}

primarily governed by the maximum path length (L_{max}) and the core node set size (V_{core}), yielding an approximate worst-case complexity of $O\left(|V_{core}|^2 \cdot \bar{k}^{L_{max}}\right)$. By aligning L_{max} with accident causation theories and pruning non-key edges, the search space is effectively contained. Thus, scalability is maintained even for larger datasets, as computation is restricted to the structurally significant sub-network rather than the exhaustive graph space.

4. Experimental analysis

4.1. Statistical analysis of maritime accident samples

The empirical basis for this study derives from a systematic analysis of 564 detailed maritime accident investigation reports. These reports, covering incidents occurring between 2019 and 2023, are sourced from the publicly available accident investigation database of the China MSA. The dataset involves vessels from multiple flag states. Specifically, the analysis encompasses a total of 1,174 ships. Among them, 650 vessels are registered in the Chinese mainland, while 524 vessels belong to other flag states, as detailed in Table 7. To ensure typicality and representativeness, selection focuses on accidents within the coastal and inland waters of China. The sample encompasses a wide range of accident types, including collision, foundering, and fire and explosion, alongside various vessel types such as cargo ships, tankers, and container ships. This provides a comprehensive, multi-faceted representation of maritime accident characteristics in Chinese waters. Consequently, the region-specific sampling strategy ensures that findings remain highly relevant and externally valid for the analysis of causal patterns within this geographical context.

To provide a macroscopic understanding of fundamental distribution patterns, a statistical analysis of sample data across four dimensions comprising accident type, vessel type, accident severity, and gross tonnage is presented. This analysis establishes a clear data profile and empirical context for subsequent causation network construction and key risk identification. Statistical results are illustrated in Fig. 3.

In addition to these statistical dimensions, a spatial analysis of accident locations provides insight into the geographical distribution of risks, as illustrated by the heatmaps in Fig. 4. The overall distribution of maritime accidents, presented in Fig. 4(a), reveals several distinct high-risk zones. Significant concentrations appear along the southeastern coast of China, particularly in the Taiwan Strait, coastal waters of Zhejiang and Fujian, and the Pearl River Delta. A secondary cluster of high accident density is also evident in the Bohai Sea. Disaggregation by accident type indicates that the geographical pattern of collisions depicted in Fig. 4(b) mirrors the overall distribution, confirming that these high-traffic and complex navigational areas constitute primary collision hotspots. Conversely, other incident types, such as foundering shown in Fig. 4(c), allision in Fig. 4(d), and fire/explosion in Fig. 4(e), exhibit more dispersed and less frequent geographical patterns, aligning with lower statistical occurrence.

Analysis of accident types reveals that collisions constitute the predominant category, accounting for 294 incidents. Other event types occur with significantly lower frequency, including 76 cases of foundering, 48 of contact, and 26 of fire and explosion. Regarding vessel involvement, cargo ships are implicated in 439 incidents, a figure consistent with their primary role in maritime transport. Oil tankers and container ships follow with 98 and 77 incidents respectively, while the involvement of fishing vessels in 45 incidents underscores potential risks

Table 7
Statistical analysis of flag states for involved vessels.

Flag State	Number of vessels	Proportion (%)
Chinese mainland	650	55.367
Hong Kong	71	0.060
Japan	43	0.037
Philippines	33	0.028
Panama	31	0.026
South Korea	27	0.023
India	26	0.022
Singapore	24	0.020
United States	15	0.013
Indonesia	15	0.013
Liberia	13	0.011
Marshall Islands	12	0.010
Norway	11	0.009
Others	203	0.173
Total	1174	-

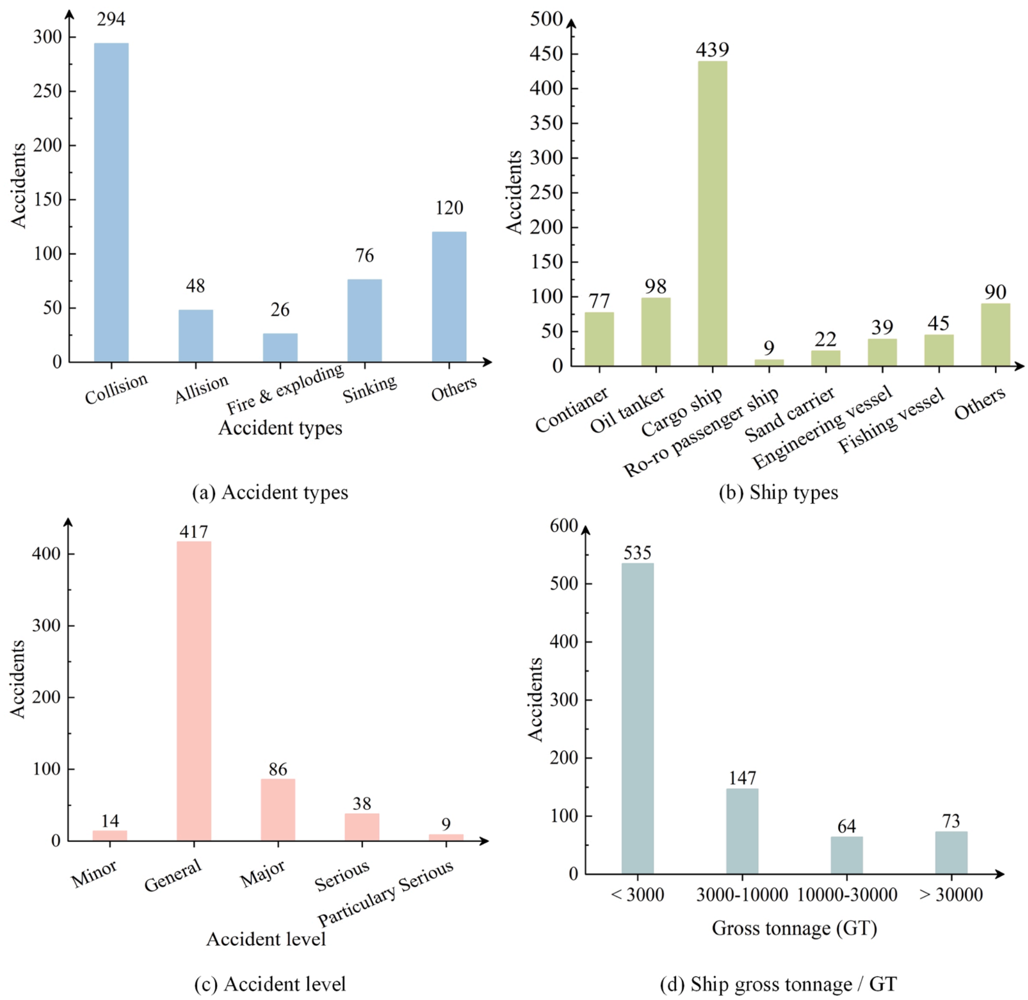


Fig. 3. Statistical distribution of maritime accident characteristics.

within mixed-traffic waters.

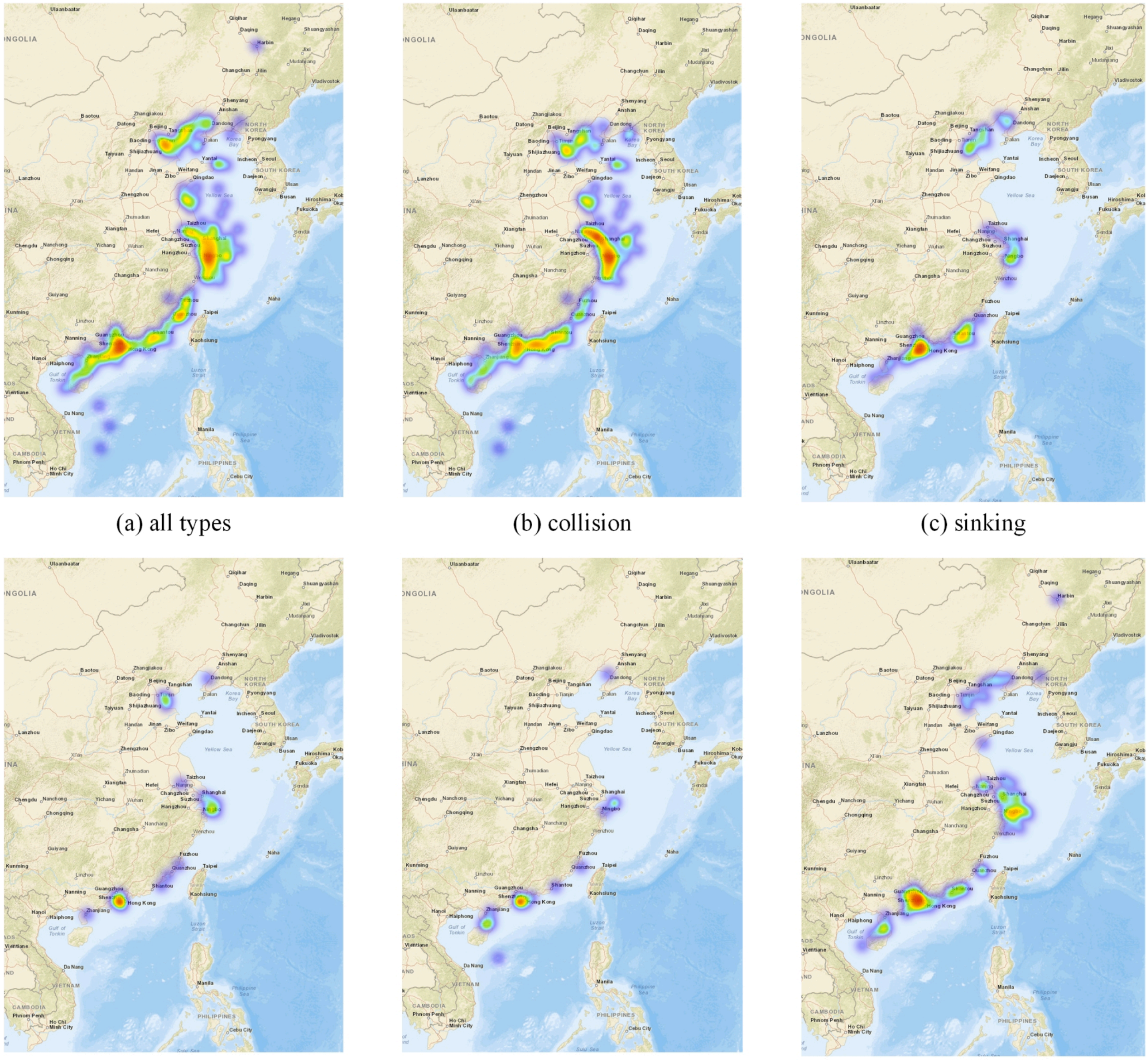
Regarding accident severity, data show a clear risk pyramid structure. Most events, numbering 417, are categorised as General incidents. Higher-severity events appear less common, comprising 86 Major and 38 Serious accidents. This distribution correlates with vessel tonnage, as the majority of accidents in the sample involve smaller vessels of <3,000 gross tonnage, with 535 such incidents recorded. Accident frequency decreases as tonnage increases, with 147 incidents involving vessels between 3,000 and 10,000 gross tonnage. Notably, incidents involving very large vessels over 30,000 gross tonnage number 73, slightly higher than the figure for vessels in the 10,000 to 30,000 gross tonnage range. This finding suggests that the manoeuvring characteristics of very large vessels present heightened risks in specific scenarios.

4.2. Construction and topological feature analysis of the causal network model

Subsequent to the macroscopic statistical analysis of the accident sample, a complex network of maritime accident causation is constructed to investigate intrinsic, non-linear interactions among causal factors. In this network, causal factors extracted from 564 accident reports are modelled as nodes, whilst identified causal relationships within each report constitute the edges. This process converts textual causal logic into a quantifiable network structure.

The resulting network comprises 39 nodes and 433 edges, wherein nodes represent core causal factors and accident outcomes, and edges signify associative relationships among them. The overall structure and association strength of the network are visualised in Fig. 5. For visual clarity, network nodes are labelled using standardised codes defined in Table 4. In this representation, each sector on the outer ring corresponds to a causal factor or accident outcome, with colour coding applied according to category (human, technology, vessel, environment, management, or accident type) to denote distinct functional risk modules. The size of each sector is proportional to the total association strength (i.e., weighted degree) of the factor. Significantly, the width of internal connecting chords is scaled proportional to edge weight, thereby visually highlighting dominant causal pathways. Factors across different categories appear extensively intertwined, with sectors for human and management factors exhibiting particular prominence, suggesting central positions within the network. Furthermore, numerous causal factors connect to the capsizing/sinking outcome, indicating that this outcome serves as a key convergence point for multiple risk pathways.

To analyse network characteristics from a quantitative perspective, macroscopic topological metrics are calculated, with results presented in Table 8. The network consists of a single connected component with a largest component ratio of 1.0, indicating that all identified core causal factors form a unified, fully connected risk system without isolated subsets. The average path length of the network stands at 1.429, a notably low value. This implies that risk propagates from any given factor to another in fewer than 1.5 steps on average. Concurrently, the network exhibits an average clustering coefficient of 0.308. The combination of a short average path length and a comparatively high clustering coefficient characterises a small-world network. This property indicates that the accident risk system possesses both high transmission



(a) all types (b) collision (c) sinking

(d) allision (e) fire & exploding (f) others

Fig. 4. Maritime accident hotspots by type.

efficiency and substantial local clustering; risk forms highly interconnected local clusters and, once initiated, propagates rapidly throughout the entire network via short pathways.

Regarding structural complexity, the network density reaches 0.294, a relatively high value correlating with the short average path length of 1.429 and the substantial clustering coefficient of 0.308. This high clustering indicates that risk factors tend to form cohesive functional modules, suggesting that effective intervention requires targeting holistic risk clusters rather than isolated errors. To substantiate the small-world property quantitatively, these metrics are benchmarked against equivalent random networks, yielding a small-worldness index greater than 1.0. This confirms that the system is tightly coupled and risk transmission is highly efficient; a latent failure propagates to a final accident node in fewer than 1.5 steps on average, leaving minimal time for intervention.

Finally, analysis of the node degree distribution reveals the presence of few highly connected hub nodes amidst many sparsely connected ones. This heterogeneity characterises a scale-free network. Such a finding provides the theoretical basis for subsequent key factor identification, suggesting that effective interventions targeting this small number of hub nodes influence the stability of the entire network substantially.

4.3. Quantitative identification of key causal factors

Subsequent to the macroscopic analysis in Section 4.2 revealing small-world and scale-free topological characteristics of the causation network, a microscopic-level investigation is conducted to identify key causal factors precisely. In accordance with the methodology detailed in Section 3.3.2, metrics including Degree, Closeness, and Betweenness Centrality are calculated for each node. Quantitative analysis is confined strictly to causal factor nodes, excluding accident outcome nodes, to ensure an accurate assessment of the role of actual causal factors within the network.

Weighted out-degree and in-degree centrality values for each causal factor are presented in Fig. 6, with x-axis labels corresponding to factor

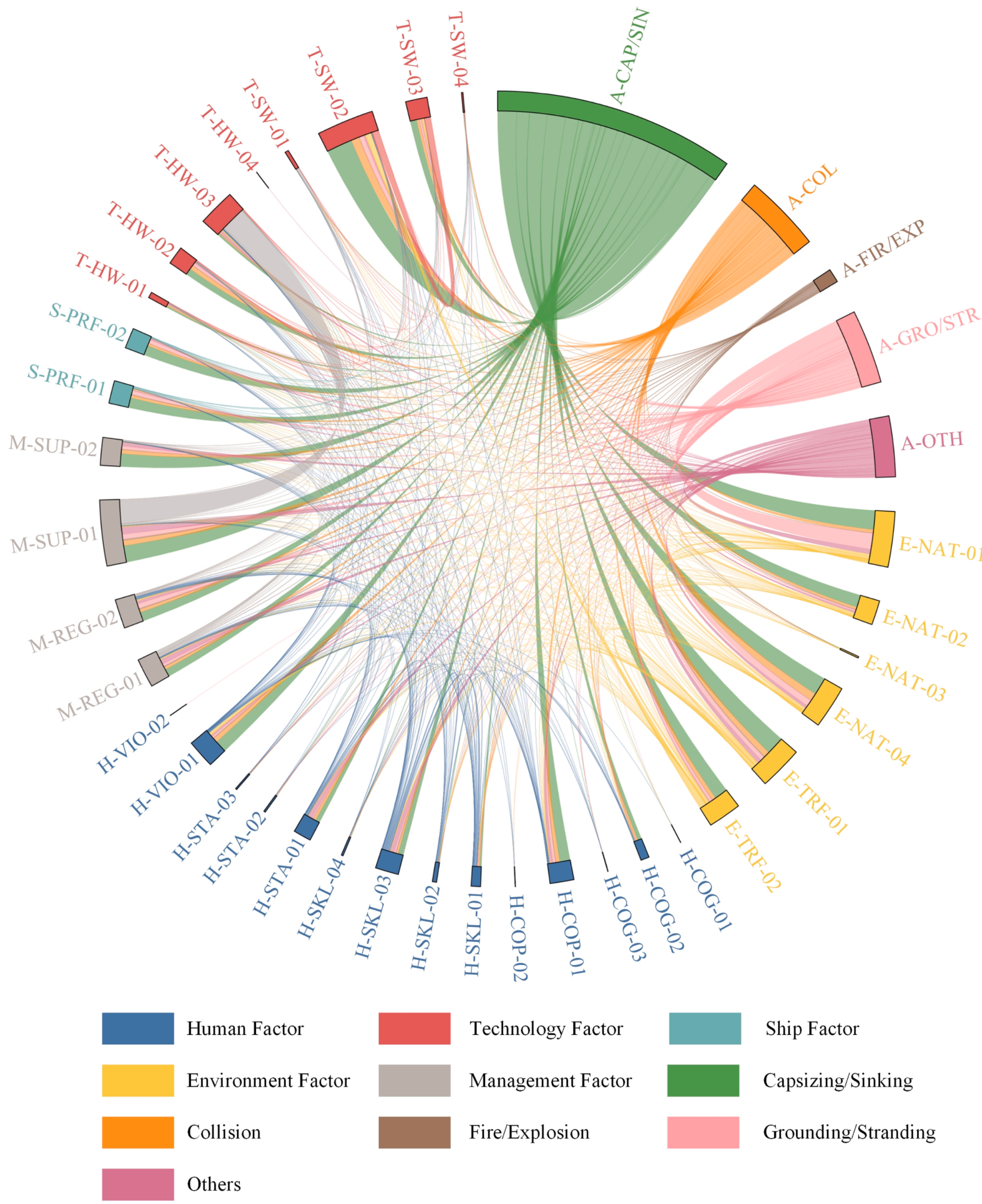


Fig. 5. The weighted co-occurrence network of maritime accident causal factors.

Table 8
Macroscopic topological characteristics of accident causation network.

Topological metric	Value
Number of nodes	39
Number of edges	433
Network density	0.294
Avg. clustering coefficient	0.308
Avg. path length	1.429
Components	1.0
Largest components ratio	1.0

codes detailed in Table 4. Nodes with high out-degree act as primary risk sources from which influence propagates widely. The highest out-degree values are observed for Sensor/Information System Failure (T-SW-02) and Adverse Weather/Sea State (E-NAT-01), indicating that technical system failures and uncontrollable environmental conditions constitute core initial triggers for subsequent chain reactions. Conversely, nodes with high in-degree function as risk convergence points towards which multiple risk pathways lead. Inadequate Supervision (M-SUP-01) exhibits the highest in-degree value, suggesting that various underlying risks from diverse origins such as personnel violations or improper equipment maintenance are attributable ultimately to deficiencies at the management and supervision level.

The distribution of centrality metrics for each factor is detailed in the radar chart in Fig. 7, wherein radial axes represent factor codes listed in

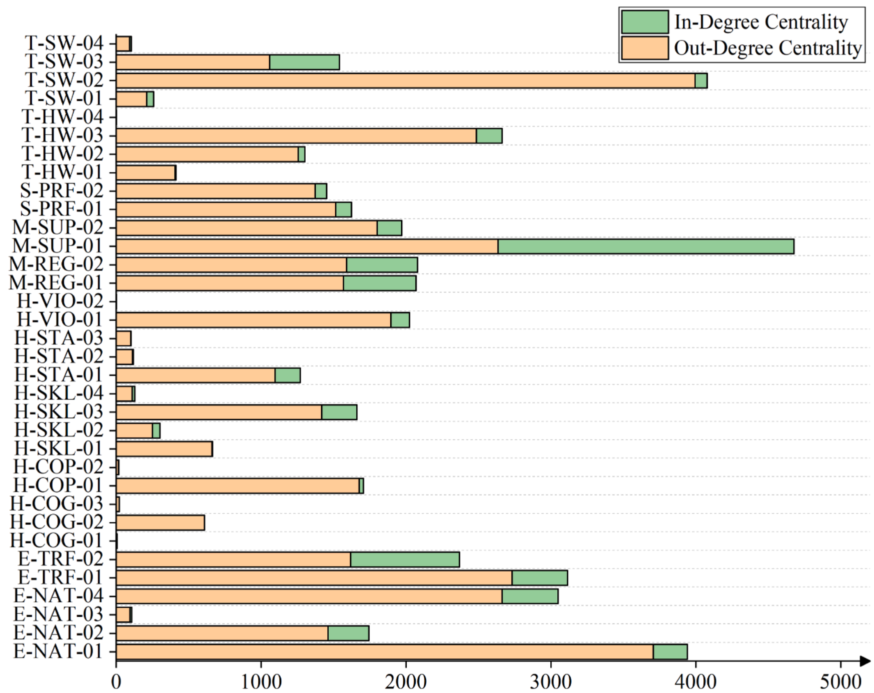


Fig. 6. Weighted degree centrality of causal factors in the maritime accident network.

Table 4. Regarding the Clustering Coefficient, factors including Inadequate Supervision (M-SUP-01), Complex Hydrographic/Channel Conditions (E-NAT-04), VTS/Shore-based Support Issues (E-TRF-02), and Sensor/Information System Failure (T-SW-02) exhibit high values. This suggests that risks associated with these factors form highly interconnected local clusters. In terms of Betweenness Centrality, factors such as Software/Algorithm Deficiencies (T-SW-01), Stability/Stowage Issues (S-PRF-02), and Violations (H-VIO-01) display elevated scores. This indicates that these factors function as critical junctures connecting distinct risk modules, serving as essential intermediaries in risk propagation between clusters. Concerning Closeness Centrality, Improper Crew Management (M-SUP-02), Manoeuvrability/Hull Issues (S-PRF-01), and Stability/Stowage Issues (S-PRF-02) appear prominent. These factors occupy central locations within the network, enabling influence over other factors across the shortest average distance, thereby facilitating high risk propagation efficiency.

To provide a comprehensive assessment of factor importance, a composite Average Importance metric is developed. Key causal factors, ranked according to this composite score, are presented in Table 9. The three factors with the highest composite importance comprise Inadequate Supervision (M-SUP-01), Stability/Stowage Issues (S-PRF-02), and Adverse Weather/Sea State (E-NAT-01), which collectively reveal a typical causal pattern in maritime accidents. Inadequate Supervision (M-SUP-01) represents a systemic, root-cause deficiency latent within organisational management, often termed a latent failure. Although not a direct accident cause, it creates conditions for the emergence of other unsafe acts and states, for instance, allowing a vessel to depart with known Stability/Stowage Issues (S-PRF-02). This inherent technical vulnerability may remain undetected in calm sea conditions. However, upon encountering an external environmental stressor such as Adverse Weather/Sea State (E-NAT-01), the latent risk is rapidly triggered and amplified, thereby compromising system stability. This evolutionary pathway, extending from a latent failure at the management level through a specific technical vessel vulnerability to an environmental trigger, demonstrates how risk propagates across hierarchical levels to result in an accident.

Beyond individual metrics, the divergence between the composite AVE and the CLUC in Table 9 highlights the practical distinction between global influence and local cohesion. Specifically, rule violation (H-VIO-01) combines a high AVE score with a low CLUC. This topological signature identifies the factor as a global diffuser that bridges otherwise unrelated subsystems, such as connecting environmental triggers to machinery failures. Such wide-ranging connectivity necessitates broad safety culture reforms to sever these transversal links. Conversely, Inadequate regulations (M-REG-01) displays the opposite pattern of lower AVE score but higher CLUC. This characterises the factor as a local cluster core driving self-reinforcing failure loops within specific functional areas like management training. Therefore, effective intervention requires targeted revisions of procedures rather than systemic measures. This differentiation aligns numerical rankings with precise management strategies, where high-importance factors demand system-wide mitigation while high-clustering factors warrant modular correction.

Edge weights in this network derive empirically from the frequency of causal links extracted via NLP. To ensure that key factor identification remains resilient to potential noise inherent in text mining or minor sampling variations, a sensitivity analysis is conducted. Random perturbations ($\pm$10%) are introduced to these empirically determined weights, and rankings are recalculated, demonstrating high stability. Specifically, Spearman's rank correlation coefficients between original and perturbed rankings consistently exceed 0.90. This confirms that the critical status of identified factors stems from the robust topological structure of the system rather than sensitivity to marginal data fluctuations.

4.4. Analysis of key risk propagation paths

While the preceding topological analysis identifies key factor nodes based on static importance, an isolated assessment of individual factors proves insufficient to fully elucidate the dynamic mechanisms of risk evolution and escalation within a complex system. The occurrence of a maritime accident constitutes not a simple aggregation of critical factors but typically follows specific propagation pathways composed of multiple factors arranged in a logical sequence. Consequently, the transition from static node importance analysis to dynamic pathway identification represents an essential step for deepening the understanding of causality

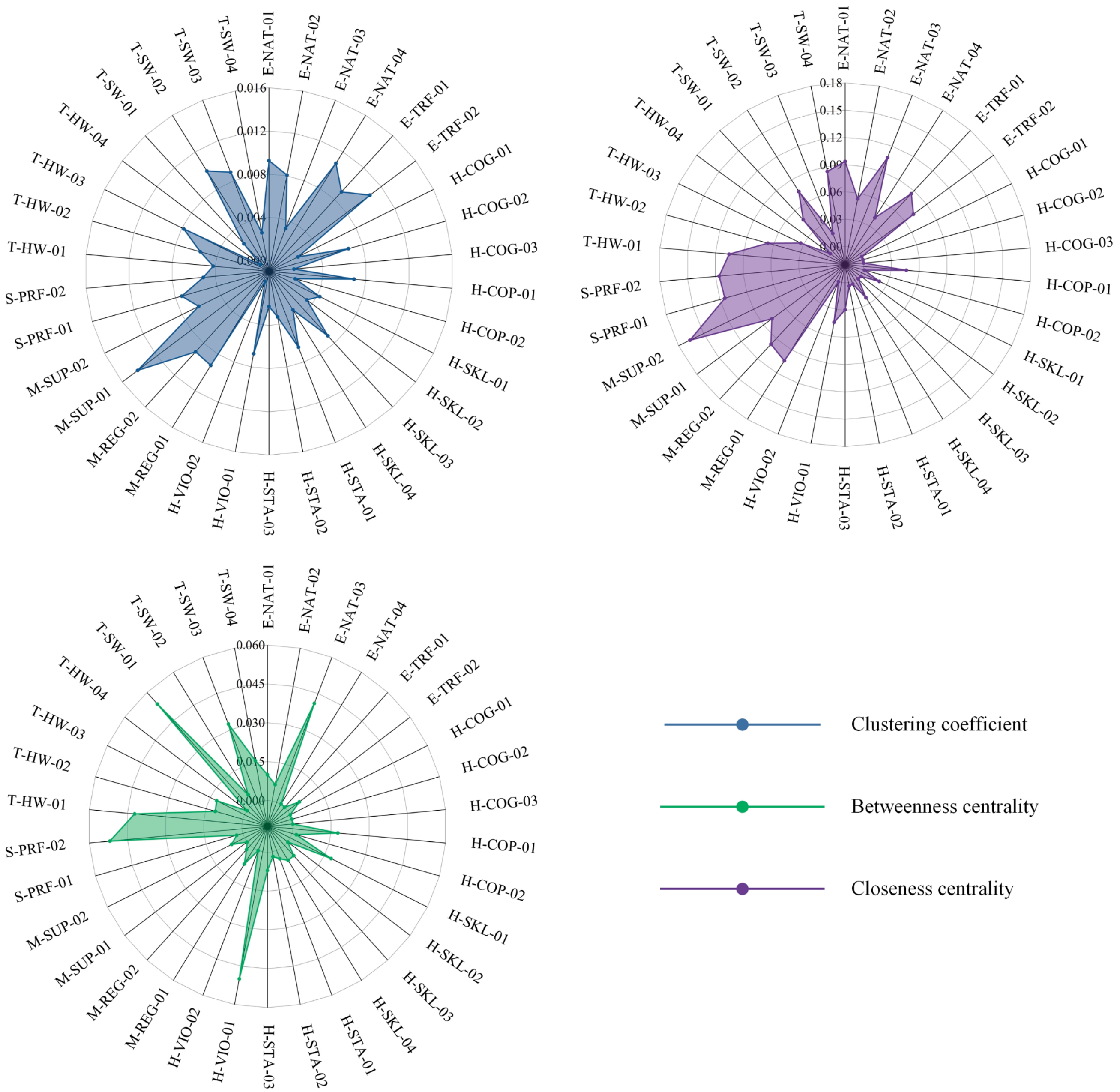


Fig. 7. Centrality profile of causal factors in the maritime accident network.

Table 9
Network centrality metrics for the key causal factors.

Factor	ODC	IDC	TDC	CLUC	BEC	CLOC	AVE
M-SUP-01	2635	2040	4675	0.014225	0	0.078685	0.426550
S-PRF-02	1372	79	1451	0.005106	0.05192	0.116053	0.408465
E-NAT-01	3706	235	3941	0.009258	0.009957	0.093653	0.358162
H-VIO-01	1895	129	2024	0.006764	0.050012	0.044408	0.346369
M-SUP-02	1800	169	1969	0.006269	0.00569	0.166378	0.327798
T-SW-02	3993	84	4077	0.009936	0.004291	0.074561	0.313776
T-HW-01	406	6	412	0.004186	0.0422	0.105263	0.303897
E-NAT-03	95	11	106	0.003246	0.040896	0.106268	0.285178
M-REG-01	1568	501	2069	0.009245	0.007112	0.104200	0.279255
E-TRF-01	2731	382	3113	0.008944	0	0.085526	0.277034

ODC: out-degree centrality; IDC: in-degree centrality;.
TDC: total degree centrality; CLUC: clustering coefficient;.
BEC: betweenness centrality; CLOC: closeness centrality; AVE: average importance.

and enabling precise risk interventions. Accordingly, the pathway identification algorithm presented in Section 3.4 is applied to mine and identify five highly representative risk evolution patterns from the complex causation network. (Fig. 8)

The analysis reveals five highly representative risk evolution patterns. The first pattern illustrates how top-level deficiencies in organisational regulations propagate to front-line technical failures. This pathway originates from Inadequate Regulations/Procedures (M-REG-01), which leads to vulnerabilities in the crew safety training system and results in Lack of Knowledge (H-SKL-02). This knowledge deficiency subsequently impairs crew cognitive processes, leading to Erroneous Judgement/Decision (H—COG-01) during stowage

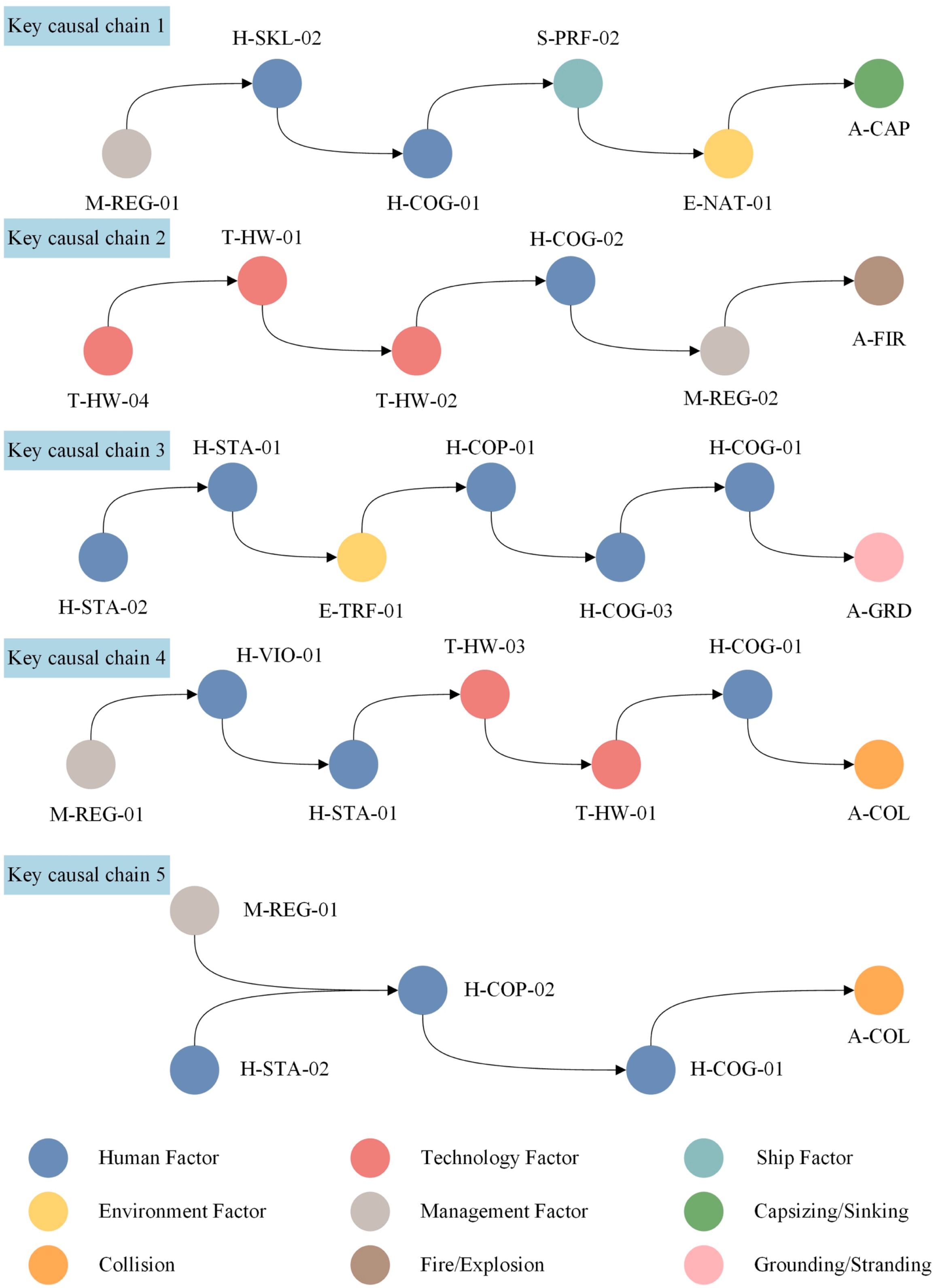


Fig. 8. Key risk propagation paths in maritime accidents.

operations. This sequence directly creates the serious safety hazard of Stability/Stowage Issues (S-PRF-02). When this latent technical vulnerability is exposed to the external environmental trigger of Adverse Weather (E-NAT-01), the safety margin of the vessel is compromised, ultimately culminating in a catastrophic Capsizing/Sinking (A-CAP) accident.

A second pathway highlights the progressive deterioration of a technical system from latent defect to functional failure. This chain commences with a Design Defect (T-HW-04), which initially manifests as a general Equipment Fault (T-HW-01). If not addressed effectively, this condition deteriorates into the failure of critical machinery, classified as Key Equipment Failure (T-HW-02). At this stage, Negligence/Oversight (H—COG-02) by the crew prevents timely recognition of the fault severity, resulting in a missed opportunity for effective intervention. This cognitive failure fully exposes the Inadequate Emergency Response Plan (M-REG-02) of the company, which results in uncontrolled escalation and triggers secondary events such as Fire/Explosion (A-FIR).

The third evolution pattern demonstrates how the deterioration of the individual state of a crew member leads to cognitive and collaborative failures. This pathway is initiated by Physiological/Psychological Fatigue (H-STA-02), a compromised state directly leading to a reduction in Safety/Vigilance Awareness (H-STA-01). When a vessel operating under this latent risk navigates into Complex Traffic Flow (E-TRF-01), environmental challenges increase substantially. Poor Communication/Coordination (H—COP-01) subsequently impedes the formation of unified situational awareness, which in turn leads to Inadequate Risk Assessment (H—COG-03). Finally, this flawed risk perception results in a critical Judgement/Decision Error (H—COG-01) by the operator, precipitating a Grounding (A-GRD) accident.

Furthermore, a fourth causal chain reveals a deep-seated coupling between front-line violations and lack of management supervision. This pathway originates from Inadequate Supervision (M-SUP-01), a systemic deficiency permitting the normalisation of Violations (H-VIO-01) and contributing to general Poor Safety Awareness (H-STA-01) among the crew. This deficient safety culture manifests in Improper Equipment Maintenance (T-HW-03), the long-term neglect of which eventually culminates in an in-transit Equipment Fault (T-HW-01). When confronted with this sudden equipment problem, the crew—habituated to violations and possessing poor safety awareness—makes an Erroneous Judgement/Decision (H—COG-01), thereby causing a Collision (A-COL) accident.

Finally, a fifth pattern illustrates a complex failure mode where team dysfunction results from the concurrent effects of organisational deficiencies and individual state issues. This pathway originates from two parallel conditions: Inadequate Regulations/Procedures (M-REG-01) provide ambiguous guidance for teamwork, whilst Physiological/Psychological Fatigue (H-STA-02) diminishes individual cognitive and performance capacity. These two multi-level risk factors converge, leading to Improper Bridge Team/Resource Management (H—COP-02), which creates significant impediments to information sharing, task delegation, and cross-monitoring. Against this backdrop of team dysfunction, the operator becomes highly susceptible to making an Erroneous Judgement/Decision (H—COG-01), which directly precipitates a Collision (A-COL) accident.

To validate empirically the identified risk propagation mechanisms, specifically the complex multi-source convergence pattern identified as key causal chain 5, the collision between the cargo vessel Huajinzhou and the container ship WAN HAI 316 on November 21, 2020, is analysed as a benchmark case. The investigation explicitly corroborates the Y-shaped causal topology extracted by the proposed model, demonstrating precise alignment between calculated high-risk nodes and factual root causes. On one branch, the shipping company failed to formulate a statutory watchkeeping schedule in compliance with rules on seafarers' watchkeeping (M-REG-01), creating a systemic gap in duty management. Simultaneously, on the other branch, the high-frequency operational rhythm of the vessel involving frequent cargo handling left the Master and chief officer with less than 10 hours of rest within the 24 hours preceding the incident, inducing severe fatigue (H-STA-02). These two streams converged at the node of improper resource management (H—COP-02), where the fatigued Master, lacking effective bridge team support, operated with compromised vigilance. This systemic breakdown directly precipitated the critical judgement error (H—COG-01) of the Master, manifesting as the erroneous identification of the opposing vessel as a crossing target and the fatal decision to turn port into the main channel. The sequence culminated in a catastrophic collision (A-COL) near the Guangzhou Port Channel. The high degree of congruence between the algorithmically identified causal chain and official investigation conclusions confirms the external validity of the network model in reconstructing real-world accident mechanisms.

5. Discussion

An integrated analytical framework combining NLP with complex network theory is presented to transform unstructured maritime accident investigation reports into a quantifiable causal network reflecting systemic risk. Topological analysis of the network reveals that the maritime accident system exhibits small-world and scale-free properties characteristic of complex systems. These properties indicate that risk propagates efficiently throughout the network via a limited number of key nodes upon initiation. Consequently, both static key causal factors and dynamic risk propagation pathways are identified. Findings are discussed regarding theoretical and managerial implications, alongside methodological contributions and limitations of the research.

5.1. Analysis of key risk propagation paths

The findings of this research offer new perspectives and contribute evidence to accident causation theory within the maritime safety domain. Small-world and scale-free properties of the causation network lend empirical support to the conceptualisation of maritime safety as a complex adaptive system. In this context, accident occurrences constitute emergent phenomena arising from non-linear interactions among various system factors rather than isolated, random events. The short average path length of 1.429 indicates high risk transmission efficiency, whilst the presence of hub nodes such as Inadequate Supervision and Sensor/Information System Failure suggests system vulnerability and sensitivity to perturbations at these key points. This finding aligns with previous research [26,48,49], which suggests that such incidents follow complex system dynamics rather than simple, linear causal chains.

Significantly, these topological features translate into specific directives for maritime safety governance. The small-world nature of the network, characterised by high local clustering and short path lengths, implies that risk propagation is rapid and challenging to contain once initiated in high-density traffic environments. This necessitates the implementation of rapid intervention protocols within safety management systems, such as proactive Vessel Traffic Service (VTS) organisation or reinforcement of the Master's overriding authority, to sever transmission links before escalation. Furthermore, the scale-free property reveals that system stability relies heavily on a limited number of hub nodes. For maritime authorities and ship operators, this dictates a transition towards risk-based preventive strategies wherein resources are concentrated on fortifying specific hub factors rather than distributing inspections or training evenly. Prioritising these hubs provides maximum leverage to disrupt the global accident network, offering a cost-effective approach to systemic risk reduction.

Furthermore, identified key risk propagation pathways reveal the dynamic transmission of risk across multiple hierarchical levels, including management, personnel, technology, and environment. This offers a data-driven interpretation of the system safety theory principle that accidents result from the interaction between latent and active failures. Whereas traditional theories often attribute accidents to the coincidental failure of multiple defensive layers, causal chains identified herein depict empirically how vulnerabilities are interconnected systematically by latent failures, such as inadequate regulations, and active failures, such as judgement errors by front-line personnel. For instance, specific pathways illustrate how high-level management deficiencies cascade to the level of personnel knowledge and operational practice, ultimately culminating in catastrophic accidents when triggered by external environmental factors. This mode of cross-level risk evolution reveals underlying organisational and managerial roots of accidents, underscoring the requirement for systematic and proactive preventive measures.

5.2. Control strategies and recommendations for the key causal chain

The key causal factors and risk propagation pathways identified in this study provide precise targets for intervention in maritime safety management. This facilitates a shift from static factor control to dynamic pathway interruption, allowing for the development of process-based, systematic preventive strategies tailored to distinct risk propagation patterns.

Regarding top-down risk propagation pathways originating from management deficiencies, the core strategy focuses on optimising the Safety Management System (SMS) to bridge the gap between regulation and practice. Operational procedures require continuous refinement to enhance practicability in complex scenarios. Significantly, SMS audits should extend beyond compliance checking to evaluate system effectiveness in blocking cross-module risk transmission. A just and transparent safety reporting culture is also essential for identifying latent failures prior to propagation to frontline operations.

For pathways of progressive deterioration initiated by technical risks, a life-cycle approach integrating human-centric design is recommended. To address strong causal links between equipment failures and subsequent human errors, vessel design and modification stages should prioritise ergonomic optimisation, thereby reducing cognitive load and preventing technology-induced errors. During the operational phase, predictive maintenance protocols utilising condition monitoring technologies require strengthening to detect incipient faults. Concurrently, crew training should cover early warning signs of critical equipment failures to counteract potential cognitive oversights during emergencies.

Concerning human-centric failure pathways, the focus lies on establishing resilient barriers against environmental pressure. Generic safety education proves insufficient; instead, scenario-based simulation training emphasising bridge resource management and situational awareness under high stress is required to sever dominant risk pathways at the source. On the regulatory side, strict enforcement of work-rest limits is essential to mitigate physiological fatigue. Furthermore, within high-density traffic waters, shore-based support systems such as VTS should provide proactive intervention, serving as an external line of defence to compensate for onboard cognitive limitations.

5.3. Contributions and limitations

A primary methodological contribution of this research involves the development and application of an integrated analytical framework that automatically constructs a quantitative causal network from unstructured text. By integrating the objective efficiency of NLP with the systemic analytical capabilities of complex network theory, fragmented and qualitative causal knowledge contained within accident investigation reports is systematically transformed into a structured model suitable for topological analysis and dynamic pathway mining. This framework enhances analytical efficiency for large-scale accident reports and offers a novel means to uncover underlying, non-linear, and networked risk evolution mechanisms often inaccessible to traditional statistical methods. Consequently, a methodological pathway bridging qualitative knowledge extraction with systemic risk modelling is provided.

Nevertheless, certain limitations delineate directions for future research. Firstly, the data selection strategy prioritises information depth, focusing on full investigation reports typically available for accidents of general grade and above. The performance of the NLP framework remains intrinsically dependent on the linguistic quality and narrative consistency of these source texts. As the dataset comprises exclusively Chinese reports, potential linguistic biases may limit direct transferability to other languages without adaptation. However, given that the analysed cases involve a significant proportion of non-Chinese flag vessels and rely on internationally standardised frameworks, such as the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) and the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW), the identified core causal mechanisms possess high external validity beyond the specific regional context. Secondly, a structural limitation concerns the exclusion of severity weighting; the current network topology is constructed based on causal frequency rather than the magnitude of accident consequences, implying that severe and minor accidents influence network structure equally. Thirdly, regarding risk dynamics, identified propagation paths represent logical causal sequences derived from textual narratives rather than physical time-series due to the absence of high-resolution timestamps. To address these constraints, future research prioritises cross-regional validation using international datasets and explores the integration of timestamped multi-source data to validate the temporal characteristics of risk evolution rigorously.

6. Conclusion

To investigate the intrinsic causal mechanisms of maritime accidents, an automated analytical framework based on 564 official accident investigation reports, integrating NLP with complex network theory, is proposed. Through this framework, key causal factors are extracted systematically from unstructured text, and a weighted, directed maritime accident causation network is constructed for quantitative analysis.

Research reveals that the maritime accident causation system exhibits small-world and scale-free properties characteristic of complex networks, indicating potential for efficient risk propagation and highlighting the pivotal role of select key factors. Through quantitative analysis of multi-dimensional centrality metrics, static risk sources of high influence, including Inadequate Supervision, Vessel Stability/ Stowage Issues, and Adverse Weather/Sea State, are identified. Furthermore, a pathway mining algorithm is employed to identify five typical risk propagation pathways. These pathways illustrate dynamically the systemic process wherein risk evolves from latent managerial failures, through technical vulnerabilities and front-line personnel actions, to major accidents upon triggering by specific environmental conditions.

To extend model applicability beyond specific regional characteristics, future research prioritises cross-jurisdictional validation using international datasets. Technologically, subsequent studies explore the integration of Large Language Models to refine semantic causal detection and incorporate resilience metrics to evaluate system recovery capabilities. Significantly, to validate temporal dynamics of risk propagation rigorously, timestamped multi-source data is integrated with sequence modelling techniques, thereby mapping identified logical causal chains onto physical time axes for predictive risk warning.

CRediT authorship contribution statement

Lichao Yang: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jingxian Liu:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Zhao Liu:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Qin Zhou:** Writing – review & editing, Validation, Supervision. **Yang Liu:** Writing – review & editing, Validation, Software, Resources, Investigation, Conceptualization. **Yukuan**

Wang: Writing – review & editing, Validation, Software, Investigation, Data curation. **Weihuang Wu:** Writing – review & editing, Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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