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Key Risk Factor Identification for Deep-Sea Transportation Safety Based on Complex Network Theory

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Abstract

Deep-sea transportation is faced with complex navigation environments, long voyages, limited emergency response resources, and interacting safety risks. Existing studies have mainly focused on individual risk factors, while the correlations and coupling effects among different factors have received insufficient attention. To identify the key risk factors affecting deep-sea transportation safety, this paper proposes a novel key factor identification model based on complex network theory. Firstly, 34 risk factors affecting deep-sea transportation safety are selected from five aspects using a literature analysis method. Secondly, a weighted directed network of risk factors is constructed based on complex network theory. Then, to evaluate the node importance, six node importance evaluation indicators are established, and a node importance evaluation method is proposed by integrating the analytic hierarchy process (AHP), technique for order preference by similarity to an ideal solution (TOPSIS), and gray relational analysis (GRA). Key risk factors are then determined according to the node importance evaluation results. Finally, the effectiveness of the proposed model is verified through a case study. The results show that the top five most critical risk factors are risk of leakage, emergency speed, physical and chemical properties of the cargoes, sense of personnel safety duty, and seasonal route. The findings can provide practical support for maritime authorities, shipping companies, and safety managers in formulating targeted prevention, control, and emergency response measures for deep-sea transportation safety.

Keywords: deep-sea transportation; complex network; key factor identification; traffic safety

1. Introduction

With the continuous expansion of global trade, maritime transportation has become increasingly active, resulting in higher vessel traffic density and more complicated navigational conditions [1], and safety risks associated with maritime transportation have become increasingly prominent. Compared with coastal or shallow-water transportation, deep-sea transportation is conducted farther from the coast and is exposed to a wider range of risk factors. Once an accident occurs, rescue forces often face difficulties in reaching the scene in a timely manner, which may result in severe losses of life and property as well as adverse environmental impacts. Therefore, the effective identification of key risk factors affecting deep-sea transportation safety has become an urgent issue to be addressed. At present, relatively limited research has been conducted on the identification of key risk factors for deep-sea transportation safety, and existing studies in this field mainly focus on deep-sea emergency response and deep-sea salvage [2–4]. Nevertheless, in the

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broader field of maritime transportation safety, the analysis of potential risk factors and the identification of key risk factors have long been important research topics in transportation safety studies [5,6], and a substantial body of research has accumulated.

In this study, risk factors are defined as potential elements that may directly or indirectly affect the safety of deep-sea transportation. These factors may arise from human, equipment, environmental, cargo, and management dimensions, and they may interact with each other through complex causal and propagation relationships. Therefore, accurately identifying risk factors and further determining key risk factors are essential for improving deep-sea transportation safety. Based on this definition, this paper reviews the literature from the following three perspectives.

(1) Identification of Maritime Transportation Risk Factors

Regarding the identification of maritime transportation risk factors, scholars have carried out studies from multiple levels and perspectives. Fan et al. [7] identified navigational risks for Maritime Autonomous Surface Ships (MASS) from four navigational stages, namely route planning, berthing and unberthing, port entry and exit, and open-sea operation, as well as four risk categories, including human, ship, environment, and technology. Wu et al. [8] reviewed the major influencing factors of maritime transportation accidents, namely human and organizational factors, covering quantitative modeling, data acquisition methods, and future research trends. Their review provides practical solutions and guidance for examining human and organizational factors. Akyuz et al. [9] conducted a systematic quantitative risk assessment of cargo liquefaction on board ships. Under a fuzzy logic setting, the bow-tie approach was adopted to examine the potential causes and consequences of failures, while fuzzy logic was used to deal with the ambiguity and imprecision of expert judgments. Zhang et al. [10] developed a theory for navigational risk recognition and screening of intelligent ships on the basis of the hierarchical holographic modeling (HHM) framework and the risk filtering, ranking, and management (RFRM) framework. They identified navigation-related risks for intelligent ships from four navigational stages, including route planning, berthing and unberthing, port entry and exit, and open-water operation, as well as four categories of risk factors, namely human, ship, environment, and management. Yi et al. [11] addressed the risk identification problem of container loss incidents during maritime transportation. They employed statistical analysis, machine learning, and clustering methods to analyze accident causes and risk levels. The results showed that adverse weather conditions were the main causative factor. Sezer et al. [12] addressed the problem of cargo tank fire risk assessment during the transportation of hazardous cargoes by chemical tankers and proposed a conceptual risk modeling method based on the Evidential Reasoning–Success Likelihood Index Method and Bayesian Belief Networks. This study further indicates that hazardous cargo characteristics, cargo tank operations, and human errors are important risk sources affecting the safety of chemical tanker transportation. Sun et al. [13] addressed the problems in maritime logistics risk assessment and proposed an integrated risk assessment model combining improved FMECA, fuzzy Bayesian networks (FBNs), and improved evidential reasoning (ER). The results showed that the priority risk events in bauxite maritime logistics were pirates or terrorist attacks, followed by workers' riots or strikes. Yu et al. [14] addressed the problem of ship collision. They first used text mining techniques to extract human factors, ship factors, natural environmental factors, and management factors from accident reports. Chi-square statistics were then applied for feature dimensionality reduction, and 33-dimensional text feature items were finally obtained to identify the causal factors of ship collision risk. Meng et al. [15] addressed the difficulty of assessing ship collision risk in Chinese waters and proposed a quantitative coupling risk assessment method for ship collisions by integrating the N–K model and Bayesian networks (BNs). Based on

304 accident reports from the China Maritime Safety Administration, they identified four major categories of risk factors: human factors, ship factors, environmental factors, and management factors. Dong et al. [16] addressed the problem of risk factor analysis for collision accidents between merchant ships and fishing vessels in coastal waters. They classified the risk factors into four categories—human factors, management factors, environmental factors, and ship factors—and used the N-K model to calculate the occurrence probability and risk values under different risk factor coupling conditions. The results showed that the coupling between ship factors and environmental factors was associated with a relatively high probability of accident occurrence.

Existing studies have identified maritime transportation risk factors from multiple perspectives and have applied various methods to analyze different maritime safety problems. These studies indicate that maritime transportation risks are mainly associated with human factors, ship or equipment conditions, environmental factors, management factors, and cargo-related factors. Among them, human errors, ship conditions, adverse environmental conditions, management deficiencies, hazardous cargo characteristics, and cargo operation processes have been widely recognized as important sources of maritime accidents.

(2) Identification of Key Risk Factors

Regarding the recognition of critical risk factors, substantial research achievements have been made in different fields. Lin et al. [17] proposed an innovative fuzzy model to identify high-risk factors in excavation in urban karst geological settings. This model integrates the interval analytic hierarchy process (I-AHP) with TOPSIS. I-AHP is used to determine criteria weights, while TOPSIS is applied to identify high-risk factors. Li et al. [18] proposed a data-oriented model to identify key factors related to fatal highway accidents by combining the non-dominated sorting genetic algorithm II (NSGA-II) with a neural network (NN) structure. Zheng et al. [19], aiming to address the insufficient accuracy of lane-changing risk recognition across various vehicle types and left/right lane-changing scenarios, developed a lane-changing risk feature dataset using the HighD high-precision vehicle trajectory data. LightGBM was then employed to rank feature importance, thereby selecting critical features that influence lane-changing risk recognition. Zhang et al. [20] established a causal network model for tower-crane accidents. Through computing network metrics such as degree, strength, and shortest path, they identified seven critical causative factors as well as three critical accident paths in tower-crane accidents. Chen et al. [21] proposed an enhanced entropy-weighted gray relational analysis (GRA) model to determine the key influencing factors of ship detention under port state control (PSC). Firstly, the improved entropy weight method was used to calculate factor weights. Subsequently, the GRA method was employed to assess the influence of each factor on the target value. Finally, the key influencing factors were determined according to the ranking results of gray relational degrees. Li et al. [22] creatively proposed an efficient approach integrating text mining, association rule mining, and Bayesian networks to deeply mine and utilize large-scale textual information from coal mine safety accident cases, thereby achieving the effective recognition of coal mine safety risk factors. However, in studies on key factor identification, researchers often pay more attention to the intrinsic logic of individual accident factors, while overlooking the interactions among different accident factors. Comprehensively considering the influence of correlations among different factors in key factor identification results can help improve the precision of key factor recognition.

(3) Key Factor Identification Based on Complex Network Theory

Due to the intricate and diverse correlations among risk factors, it is difficult to accurately quantify the logical interrelations among these factors using traditional methods. Complex networks, with their inherent network characteristics, provide an effective tool for

analyzing the associations among factors [23]. Therefore, complex network theory has been applied to the identification of key risk factors in various fields. For example, Liu et al. [24] addressed the problem of identifying key causative factors in ship collision accidents. On the basis of complex network theory, they constructed a network model associated with ship collision accidents and quantified the importance of each accident-causative factor using network efficiency, ultimately identifying the principal causal factors of ship collision accidents. Li et al. [25] developed a heterogeneous network model designed for accident cause classification on the basis of a complex network model and identified key influencing factors of railway accidents by extracting critical nodes. Wang et al. [26] addressed the difficulty of systematically identifying crucial accident causal factors and their relationships in urban rail transit systems. They developed a method for risk network construction and analysis grounded in complex network theory and constructed a risk network using 201 accident reports from urban rail transit systems in China. Li et al. [27] focused on the problem that hazardous gases in industrial working fluid systems are prone to inducing accidents and that the causal relationships of such accidents are complex. They developed a risk causation analysis framework developed by drawing on accident data and complex network theory, and constructed a complex network model according to accident chains. Kumi et al. [28] addressed the problem that safety risk factors in construction accidents are interrelated and that traditional methods are unable to comprehensively identify key risks. They constructed a co-occurrence network of safety factors using graph theory and network analysis, and identified key risk factors and risk clusters through centrality measures and community detection. Zhang et al. [29] investigated the identification of primary causal factors in ship collision accidents by integrating accident report analysis with complex network theory. They constructed a risk network pertaining to ship collision and proposed a node importance calculation method and an SSPF risk assessment method. Jiang et al. [30] addressed the problems of complex geographical conditions in port waters, frequent accidents during pilots' embarkation and disembarkation operations, and the difficulty of identifying key risk influential factors. They proposed a risk influential factor identification model for pilots' embarkation and disembarkation based on complex network theory. The results showed that pilot-related factors and management factors have significant impacts on pilotage safety, among which "insufficient pilot ladder strength" was identified as the most critical risk influential factor. Du et al. [31] addressed the identification of causal factors in collision accidents between merchant ships and fishing vessels in China's offshore waters and proposed a collision accident causation analysis method integrating association rule mining with complex network theory. The results showed that serious negligence in lookout, failure to properly assess collision risk, and failure to adopt a safe speed had significant impacts on collision accidents between merchant ships and fishing vessels. Deng et al. [32] addressed the identification of key risk factors in maritime traffic accidents along the coast of China and constructed a maritime traffic accident network model for China's coastal waters based on complex network theory. They developed a "human–ship–environment–management" risk factor network, analyzed the overall structural characteristics of the accident network using characteristic parameters of complex networks, and identified the key risk factors in maritime accidents. It can be seen that complex network theory has achieved favorable research outcomes in various fields. However, in the maritime field, existing studies mainly focus on single accident types, such as ship collisions, or specific sea areas, while its application in deep-sea transportation safety remains relatively limited. Considering the complexity and diversity of risk factors affecting deep-sea transportation safety, complex networks are suitable for quantitatively analyzing the correlations among these factors. Existing studies provide strong support for identifying the key risk factors affecting deep-sea transportation safety in this study.

Therefore, this study develops a model for the identification of critical risk factors in deep-sea transportation safety grounded in complex network theory. The main procedures and contributions are as follows:

(1) Considering the uncertainty and ambiguity of risk factors in deep-sea transportation, 34 risk factors affecting deep-sea transportation safety are selected from five dimensions.
(2) With the aid of complex network theory, a weighted directed network of deep-sea transportation risk factors is constructed by taking factors functioning as nodes and the correlations among nodes as edges.
(3) According to the topological structure of the complex network, six evaluation indicators are formulated to assess the importance of each node. The analytic hierarchy process (AHP) is adopted to determine the weight corresponding to each evaluation indicator. Then, the order preference technique based on similarity to an ideal solution (TOPSIS) is combined with gray relational analysis (GRA) to comprehensively evaluate node importance. The top five nodes in the node importance ranking are regarded as key nodes.

The innovation of this study is mainly reflected in two aspects:

(1) This study extends the research object from a single accident type or specific operational scenario commonly examined in traditional maritime risk studies to the overall safety risks of the deep-sea transportation system. Focusing on the entire process of deep-sea transportation, this study identifies the key risk factors affecting deep-sea transportation safety from a system-level perspective, reflecting a research expansion from local accident analysis to systematic risk identification.
(2) To identify the key risk factors effectively, taking the complex correlations, clear influence directions, and coupled propagation characteristics among risk factors in deep-sea transportation safety into account, a key risk factor identification framework consisting of a "weighted directed risk network–multidimensional node importance evaluation–AHP-TOPSIS-GRA comprehensive ranking" procedure is constructed in this study. Compared with existing maritime risk assessment methods, the proposed method can not only identify the individual importance of risk factors affecting deep-sea transportation safety, but also reveal the influence directions, correlation strengths, and coupled propagation relationships among risk factors, while quantifying the interactions among different risk factors. By comprehensively considering the influence of inter-factor relationships on the identification results of key risk factors, the proposed framework is more consistent with the actual evolutionary characteristics of multi-factor coupled risks in deep-sea transportation and helps to improve the scientific validity, reliability, and management relevance of key risk factor identification results.

2. Risk Factors Affecting the Safety of Deep-Sea Transportation

In this section, a literature analysis method is adopted to collect and analyze relevant data from 652 maritime transport accidents that occurred over the past decade. Statistical analysis is conducted on accident causes and related data, and the risk factors affecting deep-sea transport safety are identified and analyzed in combination with expert screening. A total of 34 risk factors were selected from five dimensions, namely personnel-related factors, equipment-related factors [33], environmental factors, cargo factors, and management-related factors, thereby establishing a relatively comprehensive risk evaluation index system.

(1) Personnel factors

Maritime experts point out that about 75%~96% of marine traffic accidents are caused by personnel factors [8], which fully reflects the important influence of personnel factors on the safety of maritime transportation.

As the main participant in the transportation process, personnel factors are the direct factor affecting the safety of deep-sea transportation [34]. Therefore, the personnel factors can be used as an important index affecting the safety of deep-sea transportation.

Personnel factors can be reflected in staffing, sense of personnel safety duty, physical and mental health, operational level of operators, ideological and political quality, personnel training, and other aspects [35].

(2) Equipment factors

The safety status of ship equipment plays an important role in risk assessment and is the most active factor next to the human factor. The condition of ship equipment determines the risk of maritime transportation to some extent. Maintaining timely and regular inspections of ship equipment during voyages is effective for reducing the probability of equipment failure, ensuring the safety of deep-sea transportation. Therefore, equipment factors are selected as an important index affecting the safety of deep-sea transportation in this paper [36].

Equipment factors mainly include the age of the vessel, ship maintainability, ship storage system safety, ship structure, deadweight of the vessel, ship stability, and ship instrumentation equipment.

(3) Navigational environment factors

In the process of deep-sea transportation, the complex marine environment also constitutes a serious threat to deep-sea transportation safety. For example, adverse weather conditions may cause ship shaking and cargo shifting, which indirectly leads to fire or leakage accidents. Therefore, environmental factors are selected as an important index affecting the safety of deep-sea transportation in this paper.

Navigational environment factors can be classified as marine natural conditions and marine traffic conditions, including wind, wave scale, visibility, ocean current, season, route distance, seasonal route, navigation aids and other indicators [37].

(4) Cargo factors

Cargo factors can be considered as controllable factors in the transport process. The loading and storage of all kinds of cargoes have a set of strict operating procedures. Due to the particularity of the maritime transportation environment, cargo is easily affected by the external environment and may be affected by moisture or even explosions, which threaten the safety of maritime transportation [38]. Therefore, cargo factors are selected as an important index affecting the safety of deep-sea transportation in this paper.

Cargo factors mainly include the physical and chemical properties of cargoes, comprehensiveness of marks and signs, quality of transportation, and risk of leakage [39].

(5) Management factors

Management factors play an important role in maritime transportation. Although they usually affect transportation safety indirectly, they are often regarded as underlying causes of accidents [40]. For example, insufficient management capabilities at the ship, company, or industry level, together with inadequate emergency plans and response measures, may increase the likelihood of accidents. Therefore, management factors are regarded as an important dimension affecting deep-sea transportation safety in this study.

Management factors mainly include security education, the construction of rules and regulations, organization of the security apparatus, emergency speed, daily status monitoring, and other related indicators.

In summary, the 34 risk factors selected from five aspects in this paper are shown in Table 1.

Table 1. Risk factors for deep-sea transportation.

Primary Index	Secondary Index
Personnel factors (E1)	Staffing (e1) Sense of personnel safety duty (e2) Physical and mental health (e3) Operation level (e4) Ideological and political quality (e5) Personnel training (e6)
Equipment factors (E2)	Age of vessel (e7) Deadweight of vessel (e8) Ship maintainability (e9) Ship Structure (e10) Safety of ship storage systems (e11) Electromechanical equipment (e12) Ship operating equipment (e13) Communication and navigation equipment (e14) Signal equipment (e15) First-aid equipment (e16) Ship stability (e17)
Environmental factors (E3)	Wind power (e18) Wave scale (e19) Visibility (e20) Ocean current (e21) Seasonal route (e22) Season (e23) Route distance (e24) Navigation AIDS (e25)
Cargo factors (E4)	Physical and chemical Properties of the cargoes (e26) Comprehensiveness of the logo and sign (e27) Shipment Quality (e28) Risk of leakage (e29)
Management factors (E5)	Security education (e30) Construction of rules and regulations (e31) Organization of the security apparatus (e32) Emergency speed (e33) Daily condition monitoring (e34)

3. Key Factor Identification Model Based on Complex Network Theory

In this part, a key factor identification framework is developed on the basis of complex network theory. Firstly, based on the 34 risk factors affecting the safety of deep-sea transportation identified in Section 2, a weighted directed risk factor network is constructed (see Section 3.1). Then, based on the structural topology of the complex network and the specific features of risk factors affecting deep-sea transportation safety, six evaluation indicators of node importance are established (see Section 3.2). Finally, a comprehensive node importance evaluation model based on AHP-TOPSIS-GRA is constructed. Node

importance is ranked, and the top five nodes are selected as the key nodes (see Section 3.3). In summary, key risk factors affecting the safety of deep-sea transport can be identified.

The specific process of identifying key risk factors is shown in Figure 1.

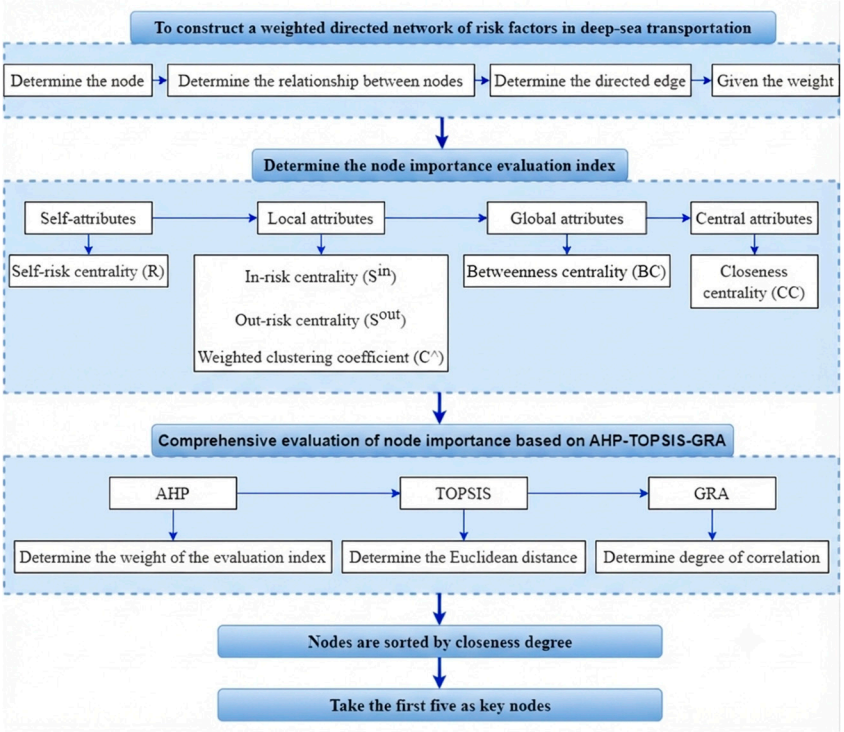


Figure 1. Key node identification model framework.

3.1. Weighted Directed Network Construction

The 34 risk factors are taken as nodes to construct the node set V; these factors were selected in Section 2 and affected the safety of deep-sea transportation. The association relationship between nodes is taken as edges to construct the edge set E. At the same time, considering the directivity of the connections among the risk factors of deep-sea transportation, as well as the difference between single risk factors and different risk factors in influencing the network structure, a weighted directed risk factor network model is established, which is represented by the graph $G = (V, E, W)$. The basic components of G include nodes, directed edges, and weights.

In the topology of the risk factor network $G = (V, E, W)$, $V = \{v_i | i \in N\}$ is the set of risk factors that function as nodes, among which $N = 1, 2, \ldots, 34$ indicates the 34 selected risk factors. $E = \{e_{ij} = (v_i, v_j) | i, j \in N\} \subseteq V \times V$ is the set of edges formed by connecting risk factor nodes. W represents the weight of the edge. For example, the weight of the directed edge (i, j) in the network can be expressed as w_{ij}.

The establishment procedure of the weighted directed network framework is described as follows:

Step 1: Determine the node. The 34 identified risk factors affecting the safety of deep-sea transportation are taken as nodes to construct node set V.

Step 2: Node empowerment. Considering that each risk factor has different effects on the risk evaluation results of deep-sea transportation, that is, each node has different effects on the network structure, weights need to be assigned to all nodes. Use the weight to represent the difference in influence degree.

Step 3: Determine the directed edge. In this study, the relationships between nodes are determined by consulting domain experts and senior engineers from relevant shipping enterprises and drawing on their professional knowledge and practical experience to

construct the directed edge set E. In the network structure, if there is an edge (i, j) from node i to node j, it means that node i influences node j. If there are edges that point towards each other between node i and node j, this indicates that they affect one another, but the degree of mutual influence may not be equal.

Step 4: Edge of empowerment. In order to quantify the difference in influence degree among different risk factors, that is, the difference in influence degree among network nodes, weights need to be assigned to the directed edges in the network. The difference in influence degree among the different risk factors is expressed through the weight. The weight of the directed edge (i, j) in the network can be expressed as w_{ij} and satisfies $0 \leq w_{ij} \leq 1, i \neq j$. The directed edge weights in the risk factor network were mainly obtained through the expert scoring method. The interval [0, 1] was divided into five equal levels to represent five grades of influence intensity. The weight value ranging from 0 to 1 indicates that the degree of association changes from weak to strong. If there is no association between node i and node j, the weight is assigned as 0; if a definite association exists between them, the weight is assigned as 1. To reduce subjective bias in expert judgment, the dispersion of expert evaluations was examined after the first round of scoring. For scoring items with large disagreement, the results were fed back to the experts for reconsideration and revision. The final edge weight was obtained by averaging the revised valid expert scores.

In conclusion, the weighted directed network model of deep-sea transportation risk factors can be constructed.

3.2. Establishment of Node Importance Evaluation Indicators

To assess the importance of each node in the weighted directed network of deep-sea transportation risk factors and identify key nodes, this section establishes a set of node importance evaluation indicators. Considering the topology of the complex network and the specific features of deep-sea transportation safety risk factors [41], six node importance evaluation indicators are constructed from four perspectives: self-attributes, local attributes, global attributes, and centrality attributes.

The selection of the six node importance indicators is based on both the topological characteristics of the weighted directed risk factor network and the practical meaning of risk propagation in deep-sea transportation safety. Self-risk centrality reflects the degree to which a risk factor itself poses a direct threat to deep-sea transportation safety. In-risk vertex strength reflects the extent to which a risk factor is induced, affected, or amplified by other preceding risk factors. Out-risk vertex strength reflects the ability of a risk factor to transmit risk to other risk factors and trigger chain reactions. Weighted clustering coefficients reflect the coupling and aggregation degree among local risk factors surrounding a given risk factor. Betweenness centrality reflects the bridging and intermediary role of a risk factor in the risk propagation path. Closeness centrality reflects the central position of a risk factor in the overall risk network and its potential influence range on other risk factors. Therefore, these six indicators can jointly characterize node importance from the perspectives of direct risk, local interaction, global propagation, and network centrality. Other commonly used network metrics, such as eigenvector centrality, PageRank, and k-shell decomposition, were not adopted as the main indicators in this study, mainly because their assumptions and interpretation are less consistent with the structure of the deep-sea transportation risk factor network. Eigenvector centrality emphasizes the influence gained by connecting with highly influential nodes, but it does not directly reflect the self-risk state or the input–output risk transmission process of a risk factor. PageRank is more suitable for networks with random-walk transition mechanisms, such as web-link networks, whereas the risk factor network in this study represents expert-judged causal or influence relationships rather than random transition probabilities. K-shell decomposition is mainly used to identify core–

periphery structures in large-scale networks, but it may weaken the role of edge direction, edge weight, and risk state values in a relatively small weighted directed risk network. Therefore, this study selects the above six indicators because they are more interpretable and more closely related to the risk generation, transmission, coupling, and propagation characteristics of deep-sea transportation safety.

The specific definitions of the six indicators are as follows:

(1) Self-risk centrality

Self-risk centrality, R_i, represents the influence degree of node itself on the safety of deep-sea transportation, which can be expressed as

$$R_i = r_i \times p_i \tag{1}$$

where $r_i (0 < r_i < 1)$ is the influence degree of this risk factor on deep-sea transportation safety, and $p_i (0 < p_i < 1)$ is the risk status value. The higher the p_i, the lower the safety of deep-sea transportation. AHP can be used to determine the influence degree of each risk factor on deep-sea transportation safety, and an expert evaluation method can be applied to determine the risk state value for each risk factor.

(2) In-risk vertex strength

To describe the interaction between nodes, denote the subscripts of nodes using $i, j, k (i, j, k = 1, 2, \ldots, 34 \; and \; i \neq j \neq k)$. Since the mutual influence between neighboring nodes is more direct, define the in-risk vertex strength S_i^{in}, the out-risk vertex strength S_i^{out}, and the weighted clustering coefficient $\hat{C}_i$ as the indexes for measuring the local influence of nodes based on the directed and weighted characteristics of the connected edges in the risk network [42,43]. Considering that risk factors are affected by their upstream adjacency factors, the in-risk vertex strength S_i^{in}, defined by Equation (2), is adopted to characterize the effect of upstream risk factor nodes on this node according to the influence degree between risk factors and the security state of upstream adjacency factors:

$$S_i^{in} = \sum_{i \in \Psi_i} w_{ji} \times p_j \tag{2}$$

where ψ_i is the set of nodes that directly affect the node, i.e., the prior neighbor nodes of node i. $w_{ji} (0 < w_{ji} < 1)$ represents the weight of influence degree from node j on node i, which can be determined using the expert scoring method. The interval [0, 1] is divided into five equal parts to represent the five levels of influence degree. The weight from 0 to 1 represents the correlation, from weak to strong. If there is no correlation between nodes i and j, the weight is 0, and if there must be a correlation, the weight is 1. This equation indicates that the more preceding neighboring nodes that node i has, the greater the effect of preceding adjacent nodes on the current node; the worse the security state of the preceding adjacent nodes, the greater the importance of this node.

(3) Out-risk vertex strength

Considering that risk factors may also influence downstream adjacency risk factors, according to the influence degree among risk factors and the risk intensity of downstream adjacency factors, the out-risk vertex strength S_i^{out} is used to describe the impact exerted by this risk factor on downstream adjacent risk factors, which is formulated as follows:

$$S_i^{out} = \sum_{i \in \varphi_i} w_{ij} \times R_j \tag{3}$$

where φ_i is the set of nodes directly affected by the node, i.e., the reachable neighboring nodes of node i. $w_{ij}(0 < w_{ij} < 1)$ denotes the weight of the degree influence from node i on node j, and is determined in the same way as above. Equation (3) indicates that the more reachable the adjacent nodes of node i, the greater the influence of this node on reachable adjacent nodes; the higher the risk level of reachable adjacent nodes, the greater the importance of this node.

(4) Weighted clustering coefficient

Since networks with higher clustering coefficients generally have faster network propagation, the weighted clustering coefficient and risk intensity of nodes are combined to define the weighted clustering coefficient $\hat{C}_i$ according to Equations (4) and (5) to quantify the effect of the interconnected closeness of neighbor nodes on risk transmission.

$$\hat{v}_{ij} = \frac{w_{ij} \times R_j}{\max\limits_{l,k}\{w_{lk} \times R_k\}} \tag{4}$$

$$\hat{C}_i = \frac{\sum\limits_{j \neq k} \hat{v}_{ij}\hat{v}_{ik}\hat{v}_{jk}}{\sum\limits_{j \neq k} \hat{v}_{ij}\hat{v}_{ik}} \tag{5}$$

The weighted clustering risk intensity of a node increases with the risk intensity of its adjacent vertices and the influence strength among vertices. Consequently, risks propagate more rapidly within the local network and exert greater local influence.

(5) Betweenness centrality

Since nodes may influence indirect adjacent nodes along certain paths, defining betweenness centrality evaluates the influence of nodes from a global perspective [44]. However, the difficulty is different, which spreads this influence relationship through different paths; it is related to the route distance among vertices and the strength of the association relationship among vertices. A shorter route distance among nodes represents a stronger association relationship among nodes and an easier spread of the influence relationship, namely for risk. The edge weights are used to represent the association relationships between nodes, i.e., the degree of influence, and higher values indicate greater influence.

Define D_l^{rs} as the length of path l between nodes r and s, used to measure the ease of risk propagation through l. It is calculated as follows:

$$D_l^{rs} = \sum_i \sum_{j \neq i} \frac{1}{w_{ij}} \times \delta_{i,j,l}^{rs} \tag{6}$$

where $\delta_{i,j,l}^{rs}$ is the correlation coefficient between the path from nodes r to s and edge (i, j). If the path passes through edge (i, j), then $\delta_{i,j,l}^{rs}$ takes 1; otherwise it takes 0.

The betweenness centrality, BC_i, which represents the global influence of node i, can be expressed as

$$BC_i = \sum_r \sum_{s \neq r} \frac{\sum\limits_{s \neq t \neq r} n_{rs}^l / g_{rs}}{\sum\limits_{l \in l_{rs}} 1/D_l^{rs}} \tag{7}$$

where n_{rs}^l represents the number of paths which pass through node i, along the g_{rs} path, and from node r to node s. g_{rs} is the number of paths from node r to node s.

(6) Closeness centrality

It is assumed that the greater the closeness centrality of a vertex within the network, the nearer it is to the network center and the more significant the node located at the center

is than the node on the edge. This is because a larger closeness centrality value for a node indicates that it is closer to other nodes, and it is easier to observe information transmission within the network. The closeness centrality of a node is defined as the multiplication of the reciprocal of d_i and the self-risk centrality, which can indicate the relative significance of nodes within the network [45]. Within the weighted network structure, as edge weights are different, according to the principle of assigning similar weights, the larger the weight, the shorter the distance and the closer the relationship.

Suppose that the edge weight of (i, j) is w_{ij}; then, define the edge length as $1 \Big/ w_{ij}$. When node i can reach node j only through edges (i, k) and (k, j), then the shortest path distance d_{ij} between nodes i and j can be written as

$$d_{ij} = 1 \Big/ w_{ik} + 1 \Big/ w_{kj} \tag{8}$$

So,

$$CC_i = \frac{1}{d_i} = \frac{N}{\sum_{i=1}^{N} d_{ij}} \times R_i \tag{9}$$

where d_i is the average distance between this node and its neighbors. The closer a node is to the network center, the greater its influence on other nodes.

In summary, the self-risk centrality R, in-risk vertex strength S^{in}, out-risk vertex strength S^{out}, weighted clustering coefficient $\hat{C}$, betweenness centrality BC, and closeness centrality CC of nodes are selected as evaluation indexes of node importance from four aspects in this paper. However, evaluating node importance only through these specific indicators may be insufficient in actual complex networks. To achieve a more comprehensive and objective assessment of node importance, the evaluation method of node importance will be improved by combining it with other evaluation methods.

3.3. A Comprehensive Evaluation Model of Node Importance Based on AHP-TOPSIS-GRA Is Constructed

In this section, in order to evaluate node importance comprehensively and objectively, an evaluation model of node importance is proposed, which is comprehensive and based on AHP-TOPSIS-GRA.

Firstly, the analytic hierarchy process (AHP) integrates quantitative and qualitative analysis, enabling expert opinions to be effectively captured and the weights of evaluation indicators to be accurately determined [46]. Using the AHP method to calculate the weights of the six node importance evaluation indicators allows the relative importance among these indicators to be reasonably reflected, thereby laying a foundation for the subsequent comprehensive evaluation of node importance by integrating the six indicators. Therefore, based on the six node importance evaluation indicators established above, this study adopts the AHP method to determine the weight of each evaluation indicator.

Subsequently, the weighted-sum method mainly obtains the comprehensive score by linearly aggregating normalized indicators, which may weaken the structural differences among different indicators and cannot fully reflect the relative distance and degree of difference between each node and the ideal key risk factors. Meanwhile, the basic principle of TOPSIS is to find the positive and negative ideal solutions of each indicator, and then measure the closeness between the indicator and the positive and negative ideal solutions, on this basis ranking the nodes [47]. The comparison in the calculation process needs to use all the raw data; the original data are fully utilized. Therefore, TOPSIS is suitable for the complex network framework of risk elements affecting deep-sea transportation safety

established in this paper. However, the TOPSIS method has some limitations; it is easily affected by abnormal values and relies on data, which may cause bias in the assessment results. Moreover, the TOPSIS method mainly evaluates alternatives by computing the Euclidean distance between each object and the positive or negative ideal solution. However, the correlation between indicators may make the Euclidean distance equal, resulting in limitations that cannot be clearly distinguished, and the distance only reflects the position relationship between data curves.

To compensate for the shortcomings of the TOPSIS method, the GRA method was used to improve TOPSIS. GRA is a multi-criteria decision model for effectively evaluating a large amount of uncertain information [48]. This model has simple operation and does not need to rely on data excessively, which can better address the issue that the evaluation index is difficult to quantify and count accurately. Therefore, applying GRA to assess risk factors can reduce imprecise information and make up for systematic limitations. In addition, GRA mainly ranks evaluation alternatives by calculating the gray relational degree between each alternative and the positive ideal solution, which can reflect the shape changes in the data. Therefore, this study combines TOPSIS with GRA to propose an improved integrated evaluation method that incorporates both static distance and dynamic trend analysis. By maximizing the advantages of both methods, the proposed approach helps improve the accuracy of node importance evaluation results.

In conclusion, the AHP-TOPSIS-GRA approach is adopted to comprehensively assess risk factor nodes. For the problem of equal Euclidean distances between the positive ideal scheme and negative ideal scheme, the TOPSIS method is improved by using a virtual negative ideal scheme instead of a negative ideal scheme, thereby making the importance evaluation result more accurate.

The specific steps of risk factor importance evaluation are as follows:

Step 1: The AHP method was used to determine the weights of each importance evaluation index, i.e., $w = (w_1, w_2, w_3, w_4, w_5, w_6)$.

Step 2: Standardize the evaluation units. Each evaluation index corresponds to each risk factor, which is regarded as an evaluation unit. x_{im} is used to denote the evaluation unit corresponding to the mth metric value of node i, where i denotes the network node and $i = 1, 2, \ldots, 34$; $m = 1, 2, \ldots, 6$ denotes the self-risk intensity, in-risk intensity, out-risk intensity, weighted aggregation risk intensity, betweenness centrality and closeness centrality. The above attribute values are positively correlated with the node importance and positively normalized for the evaluation unit, which is

$$y_{im} = \frac{x_{im} - \min\{x_{im}\}}{\max\{x_{im}\} - \min\{x_{im}\}} \tag{10}$$

where y_{im} is the normalization matrix of the evaluation unit.

Step 3: The weighted standardized decision matrix $Z = (z_{im})_{a \times b}$ was constructed. According to $z_{im} = y_{im} \times w_m$, the positive ideal scheme Z^+ and the negative ideal scheme Z^- are calculated and determined as

$$Z^+ = \max\{z_1^{\max}, z_2^{\max}, \ldots, z_6^{\max}\} \tag{11}$$

$$Z^- = \min\left\{z_1^{\min}, z_2^{\min}, \ldots, z_6^{\min}\right\} \tag{12}$$

where $z_m^{\max} = \max_i\{z_{im}\}$ and $z_m^{\min} = \min_i\{z_{im}\}$.

Step 4: In order to solve the problem of equal Euclidean distances between the positive and negative ideal schemes, which often appear in the TOPSIS method, a virtual negative ideal scheme is introduced to replace the original negative ideal scheme. The virtual

negative ideal solution is to find an ideal point on the extension line of the positive ideal solution and the negative ideal solution, and make it satisfy this equation: $z_m^{-*} = 2z_m^- - z_m^+$.

According to the following equations, the Euclidean distance d_i^+ to the positive ideal solution and the Euclidean distance d_i^- to the virtual negative ideal solution for each evaluation unit can be calculated separately.

$$d_i^+ = \sqrt{\sum_{m=1}^{6} \left(z_{im} - z_m^+\right)^2} \tag{13}$$

$$d_i^- = \sqrt{\sum_{m=1}^{6} \left(z_{im} - z_m^{-*}\right)^2} \tag{14}$$

Step 5: The correlation coefficient r_{im}^+ for each evaluation unit relative to the positive ideal solution and the correlation coefficient r_{im}^- relative to the virtual negative ideal solution can be obtained separately based on the following equations.

$$r_{im}^+ = \frac{\min|z_m^{\max} - z_{im}| + \rho\max|z_m^{\max} - z_{im}|}{|z_m^{\max} - z_{im}| + \rho\max|z_m^{\max} - z_{im}|} \tag{15}$$

$$r_{im}^- = \frac{\min|z_m^{\min} - z_{im}| + \rho\max|z_m^{\min} - z_{im}|}{|z_m^{\min} - z_{im}| + \rho\max|z_m^{\min} - z_{im}|} \tag{16}$$

Step 6: The correlation r_i^+ with the positive ideal solution and the correlation r_i^- with the negative ideal solution can be calculated separately for each evaluation unit according to the following equations.

$$r_i^+ = \frac{1}{6}\sum_{m=1}^{6} r_{im}^+ \tag{17}$$

$$r_i^- = \frac{1}{6}\sum_{m=1}^{6} r_{im}^- \tag{18}$$

Step 7: To remove the influence of different dimensions, normalize the degree for correlation and Euclidean distance.

$$R_i^+ = \frac{r_i^+}{\max r_i^+}$$

$$R_i^- = \frac{r_i^-}{\max r_i^-}$$

$$D_i^+ = \frac{d_i^+}{\max d_i^+}$$

$$D_i^- = \frac{d_i^-}{\max d_i^-}$$

Step 8: The closeness of each node relative to the positive ideal solution S_i^+ and the negative ideal solution S_i^- can be calculated separately according to the following equations; for convenience, let $\alpha = 0.5$.

$$S_i^+ = \alpha R_i^+ + (1-\alpha) D_i^- \tag{19}$$

$$S_i^- = \alpha R_i^- + (1-\alpha) D_i^+ \tag{20}$$

Step 9: Fitting progress, C_i^+, can be defined as

$$C_i^+ = \frac{S_i^+}{S_i^+ + S_i^-} \tag{21}$$

The higher the closeness value, the greater the significance of risk factor nodes.

In summary, the critical risk factors influencing the safety of deep-sea transportation can be determined by ranking the risk factor nodes.

4. Case Study

In this section, a transportation example C, which is in a deep-sea area A in the South China Sea, is taken as an application case to determine the key risk factors affecting the safety of deep-sea transportation, and the proposed content is applied to the research. A total of 12 experts were invited to participate in the evaluation. The experts were mainly from the fields of maritime supervision, shipping company safety management, dangerous goods transportation, ship operation management, and maritime safety risk assessment research. All experts had more than five years of relevant practical or research experience and were able to accurately judge the causal relationships and influence strengths among risk factors affecting deep-sea transportation safety. The selection of experts mainly followed the following criteria: firstly, they had professional knowledge of maritime transportation safety, dangerous goods transportation, ship operation management, or risk assessment; secondly, they had relevant industry practice or research experience; thirdly, they were familiar with the mechanisms of personnel-, equipment-, environment-, cargo-, and management-related risk factors in deep-sea transportation. In this study, the degree of consensus was measured using the coefficient of variation and the consistency ratio.

4.1. Construction of a Weighted Directed Network Model for Transportation Risk Factors in Sea Area A

Firstly, 34 risk factors are regarded as network nodes, as selected in Section 2 of this paper. Then, we determine the association relationship and influence degree among the nodes in the network using the expert investigation method (Delphi method). Finally, the weighted directed network of risk factors for transportation in sea area A is established, as shown in Figure 2.

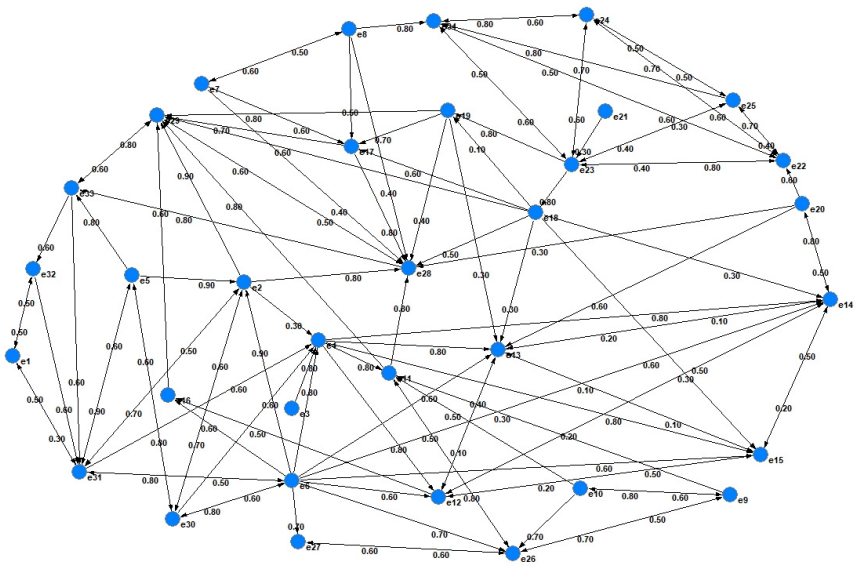


Figure 2. Weighted directed network.

The blue dots in the figure represent the 34 risk factors selected in this paper. Directed edges represent the influence between the factors, and the number of directed sides represents the weight, which indicates the difference in the influence degree between different risk factors. The node-to-node relationships and associated directed edge weights among the 34 risk factors are shown in the following Table 2.

Table 2. Node-to-node relationships and associated directed edge weights among the 34 risk factors.

Tail Node	Target Nodes (Weight)
e1	e31 (0.3), e32 (0.5)
e2	e4 (0.3), e28 (0.8), e29 (0.9), e30 (0.7), e31 (0.7)
e3	e4 (0.8)
e4	e11 (0.8), e12 (0.8), e13 (0.8), e14 (0.8), e15 (0.8)
e5	e2 (0.9), e30 (0.8), e31 (0.9), e33 (0.8)
e6	e2 (0.9), e4 (0.8), e12 (0.6), e13 (0.6), e14 (0.6), e15 (0.6), e16 (0.6), e26 (0.7), e27 (0.7), e30 (0.8), e31 (0.8)
e7	e8 (0.5), e17 (0.6), e28 (0.4),
e8	e7 (0.6), e17 (0.5), e28 (0.4), e34 (0.8)
e9	e10 (0.8), e11 (0.3), e26 (0.7)
e10	e9 (0.6), e11 (0.5), e26 (0.7)
e11	e26 (0.8), e28 (0.8), e29 (0.8)
e12	e13 (0.4), e14 (0.5), e15 (0.5), e16 (0.5)
e13	e12 (0.1), e14 (0.1), e15 (0.1)
e14	e12 (0.2), e13 (0.2), e15 (0.2), e20 (0.8)
e15	e12 (0.2), e13 (0.1), e14 (0.5)
e16	e29 (0.6)
e17	e28 (0.5), e29 (0.7)
e18	e13 (0.3), e14 (0.3), e15 (0.3), e17 (0.6), e19 (0.1), e28 (0.5), e29 (0.6)
e19	e13 (0.3), e17 (0.7), e28 (0.4), e29 (0.8)
e20	e13 (0.6), e14 (0.5), e22 (0.6), e28 (0.3)
e21	e23 (0.3)
e22	e23 (0.4), e24 (0.7), e25 (0.7), e34 (0.5)
e23	e18 (0.8), e19 (0.8), e22 (0.8), e24 (0.7), e25 (0.3), e34 (0.5)
e24	e22 (0.6), e23 (0.6), e25 (0.5), e34 (0.8)
e25	e22 (0.4), e23 (0.4), e24 (0.5), e34 (0.8)
e26	e9 (0.5), e11 (0.5), e27 (0.6)
e27	e26 (0.6)
e28	e29 (0.6), e33 (0.8)
e29	e28 (0.5), e33 (0.6)
e30	e2 (0.6), e4 (0.6), e5 (0.6), e6 (0.6)
e31	e1 (0.5), e2 (0.5), e4 (0.6), e5 (0.6), e6 (0.5)
e32	e1 (0.5), e31 (0.6)
e33	e29 (0.8), e31 (0.6), e32 (0.6)
e34	e22 (0.6), e23 (0.6), e24 (0.6)

4.2. Identification of Key Risk Factors for Transportation Safety in Sea Area A

Based on the constructed weighted directed network of transport risk factors in sea area A and the key factor identification model proposed in Section 3, the key factors are identified as follows.

(1) Calculate the node importance evaluation index value

According to the actual situation of transportation event C in sea area A, an expert grading method was used to judge the degree of influence of each risk factor on the safety of deep-sea transportation through subjective comparison using the domain knowledge of experts. Then, the initial weights corresponding to individual factors were calculated using the AHP method; the details are shown in Table 3.

Table 3. Initial weight of risk factors.

Dimension / Weight Factor	E1	E2	E3	E4	E5	Weight Initialization
	0.2615	**0.0333**	**0.1290**	**0.5128**	**0.0634**	
e1	0.0284					0.0074
e2	0.4410					0.1153
e3	0.0463					0.0121
e4	0.2395					0.0626
e5	0.1601					0.0419
e6	0.0847					0.0221
e7		0.0179				0.0006
e8		0.0256				0.0009
e9		0.0785				0.0026
e10		0.0441				0.0015
e11		0.1964				0.0065
e12		0.3429				0.0114
e13		0.1057				0.0035
e14		0.0491				0.0016
e15		0.0238				0.0008
e16		0.1052				0.0035
e17		0.0107				0.0004
e18			0.2367			0.0305
e19			0.1317			0.0170
e20			0.0960			0.0124
e21			0.0509			0.0066
e22			0.2356			0.0304
e23			0.0447			0.0058
e24			0.1160			0.0150
e25			0.0884			0.0114
e26				0.2895		0.1485
e27				0.0849		0.0435
e28				0.0425		0.0218
e29				0.5831		0.2290
e30					0.2615	0.0166
e31					0.1290	0.0082
e32					0.0634	0.0040
e33					0.5218	0.0325
e34					0.0333	0.0021

In Table 3, E1, E2, . . ., E5 represent the human factors, equipment factors, environment factors, cargo factors, and management factors, respectively; e1, e2, . . ., e34 represent the 34 potential risk factors selected, and the specific meanings are shown in Table 1. The consistency ratio of each judgment matrix is shown in Table 4. It can be seen from the table that the CR values of all judgment matrices are less than 0.10, indicating that all judgment matrices pass the consistency test.

Table 4. Consistency ratios of judgment matrices.

Judgment Matrix	Order (n)	CR
V	5	0.053
V_1	6	0.057
V_2	11	0.068
V_3	8	0.084
V_4	4	0.061
V_5	5	0.053

Finally, the expert investigation method (Delphi method) is employed to ascertain the risk state value associated with each risk factor and the degree of interaction between adjacent nodes, and the self-risk centrality R, in-risk centrality S^{in}, out-risk centrality S^{out}, weighted clustering coefficient $\hat{C}$, betweenness centrality BC, and closeness centrality CC of each node, which are calculated according to Equations (1), (2), (3), (5), (7), and (9), respectively. Table 5 summarizes the results derived from the calculations.

Table 5. Calculation results of six importance evaluation indexes corresponding to each risk factor.

Factor	R	S^{in}	S^{out}	$\hat{C}$	BC	CC
e1	0.0148	4	0.0178	0.0074	0.0000	0.0022
e2	0.2306	8.9	0.6975	0.0780	0.0055	0.0476
e3	0.0726	0	0.1002	0.0000	0.0000	0.0131
e4	0.1252	11.8	0.0571	0.0348	0.0202	0.0288
e5	0.1257	4.8	0.3942	0.0483	0.0019	0.0273
e6	0.0442	4.4	0.6933	0.0093	0.0095	0.0136
e7	0.0030	2.4	0.0284	0.0015	0.0000	0.0005
e8	0.0036	2.5	0.0300	0.0010	0.0000	0.0006
e9	0.0052	2.8	0.2174	0.0033	0.0002	0.0006
e10	0.0045	1.6	0.2208	0.0036	0.0000	0.0006
e11	0.0195	4.7	0.7683	0.0049	0.0024	0.0030
e12	0.0342	4.3	0.0131	0.0197	0.0010	0.0053
e13	0.0105	8.5	0.0041	0.0046	0.0002	0.0007
e14	0.0048	8.7	0.0491	0.0021	0.0011	0.0007
e15	0.0024	5.8	0.0103	0.0015	0.0000	0.0003
e16	0.0105	2.7	0.3588	0.0017	0.0003	0.0013
e17	0.0008	7.6	0.4709	0.0003	0.0000	0.0001
e18	0.0610	3.2	0.4007	0.0163	0.0056	0.0107
e19	0.0340	3.4	0.5083	0.0102	0.0022	0.0050
e20	0.0496	2.4	0.1013	0.0110	0.0106	0.0086
e21	0.0264	0	0.0070	0.0000	0.0000	0.0032
e22	0.1216	11	0.1002	0.0836	0.0204	0.0170
e23	0.0232	8.2	0.2369	0.0102	0.0047	0.0232
e24	0.0600	9.2	0.1228	0.0550	0.0001	0.0092
e25	0.0684	6	0.0896	0.0684	0.0000	0.0095

Table 5. *Cont.*

Factor	R	S^{in}	S^{out}	$\hat{C}$	BC	CC
e26	0.2970	8.5	0.0646	0.0713	0.0263	0.0378
e27	0.0870	2.6	0.1782	0.0435	0.0000	0.0094
e28	0.0654	13.2	0.4628	0.0127	0.0133	0.0105
e29	0.5980	15.2	0.1107	0.1182	0.1097	0.0906
e30	0.0664	5.4	0.3154	0.0221	0.0008	0.0161
e31	0.0328	11.1	0.2953	0.0061	0.0144	0.0080
e32	0.0160	3.4	0.0271	0.0080	0.0002	0.0029
e33	0.1300	6	0.5077	0.0325	0.0534	0.0263
e34	0.0021	15.2	0.1229	0.0015	0.0000	0.0003

(2) Determine node importance evaluation index weights

The outcomes of determining the node importance evaluation index weight through the AHP method are summarized in Table 6.

Table 6. Importance evaluation index weights obtained using the AHP method.

Importance Evaluation Index	Weight
Self-risk intensity	0.1998
In-risk intensity	0.0855
Out-risk intensity	0.0811
Weighted clustering coefficient	0.2219
Betweenness centrality	0.3460
Proximity	0.0657

(3) Node Importance Comprehensive Evaluation

The node importance is evaluated comprehensively based on TOPSIS-GRA.

Step 1: Regard each evaluation index corresponding to each risk factor in Table 5 as an evaluation unit. The evaluation unit is standardized according to Equation (10).

Step 2: The weighted standardized decision matrix is formulated, followed by the determination of the positive ideal scenario and the negative ideal scenario.

Step 3: For the problem of Euclidean distance equality between the positive ideal alternative and the negative ideal alternative, a virtual negative ideal scheme is used to replace the negative ideal scheme, and the TOPSIS method is improved to make the evaluation result of node importance more accurate. Calculate the Euclidean distances d_i^+ and d_i^- according to Equations (13) and (14), respectively; Table 7 provides the corresponding results.

Table 7. Ranking of risk factors.

Factor	d_i^+	d_i^-	r_i^+	r_i^-	S_i^+	S_i^-	C_i^+	Ranking
e1	0.4641	0.4901	0.5675	0.8192	0.5577	0.9849	0.3615	28
e2	0.3620	0.6298	0.7102	0.7365	0.7067	0.8270	0.4608	4
e3	0.4641	0.4903	0.5668	0.8194	0.5574	0.9850	0.3614	29
e4	0.3706	0.5887	0.6364	0.7712	0.6461	0.8571	0.4298	6
e5	0.4060	0.5613	0.6300	0.7746	0.6282	0.8966	0.4120	8
e6	0.4275	0.5351	0.6245	0.7852	0.6115	0.9258	0.3978	12

Table 7. *Cont.*

Factor	d_i^+	d_i^-	r_i^+	r_i^-	S_i^+	S_i^-	C_i^+	Ranking
e7	0.4722	0.4812	0.5599	0.8256	0.5490	0.9973	0.3550	33
e8	0.4723	0.4811	0.5602	0.8254	0.5491	0.9974	0.3551	32
e9	0.4667	0.4878	0.5718	0.8167	0.5587	0.9862	0.3617	27
e10	0.4679	0.4864	0.5688	0.8189	0.5564	0.9888	0.3601	30
e11	0.4526	0.5141	0.6226	0.7921	0.5993	0.9564	0.3852	16
e12	0.4487	0.5070	0.5759	0.8115	0.5710	0.9640	0.3720	22
e13	0.4643	0.4932	0.5797	0.8135	0.5658	0.9817	0.3656	24
e14	0.4644	0.4934	0.5816	0.8124	0.5668	0.9811	0.3662	23
e15	0.4701	0.4851	0.5689	0.8200	0.5558	0.9917	0.3591	31
e16	0.4652	0.4910	0.5803	0.8118	0.5649	0.9817	0.3652	25
e17	0.4645	0.4970	0.6014	0.8011	0.5792	0.9744	0.3728	21
e18	0.4313	0.5252	0.5992	0.7952	0.5929	0.9357	0.3879	14
e19	0.4479	0.5110	0.5996	0.7987	0.5856	0.9554	0.3800	19
e20	0.4307	0.5224	0.5773	0.8087	0.5800	0.9433	0.3807	18
e21	0.4726	0.4806	0.5549	0.8293	0.5460	1.0000	0.3532	34
e22	0.3427	0.6369	0.6636	0.7604	0.6859	0.8210	0.4552	5
e23	0.4415	0.5163	0.6043	0.7938	0.5909	0.9457	0.3845	17
e24	0.4188	0.5537	0.6192	0.7849	0.6186	0.9163	0.4030	10
e25	0.4137	0.5653	0.6164	0.7873	0.6232	0.9124	0.4058	9
e26	0.3091	0.6588	0.6716	0.7506	0.7017	0.7796	0.4737	3
e27	0.4255	0.5379	0.5964	0.7962	0.5982	0.9302	0.3914	13
e28	0.4099	0.5546	0.6419	0.7741	0.6309	0.9004	0.4120	7
e29	0.0698	0.9437	0.9521	0.6781	1.0000	0.4827	0.6744	1
e30	0.4364	0.5220	0.6034	0.7922	0.5934	0.9393	0.3872	15
e31	0.4209	0.5398	0.6157	0.7881	0.6094	0.9204	0.3983	11
e32	0.4633	0.4907	0.5668	0.8194	0.5577	0.9841	0.3617	26
e33	0.2958	0.6658	0.6594	0.7551	0.6990	0.7683	0.4764	2
e34	0.4651	0.5028	0.6135	0.8005	0.5886	0.9747	0.3765	20

Step 4: Calculate the correlation coefficients r_{im}^+ and r_{im}^- using Equations (15) and (16).

Step 5: Calculate correlations r_i^+ and r_i^- using Equations (17) and (18); the corresponding results are reported in Table 7.

Step 6: Normalize the correlation r_i and the Euclidean distance d_i to eliminate the effect of different dimensions.

Step 7: Calculate proximities S_i^+ and S_i^- using Equations (19) and (20); Table 7 summarizes the corresponding results.

Step 8: According to Equation (21), the degree of closeness C_i^+ is calculated and ranked; the results are shown in Table 7.

4.3. Result Analysis

The greater the degree of node closeness in the network, the greater the importance of the nodes. As shown in Table 7, the highest closeness centrality of risk factors is 0.6744, which is the factor for risk of leakage. Therefore, risk of leakage is the most critical factor affecting transportation safety identified using the model developed in this study, and the other risk factors in the top five are emergency speed, physical and chemical properties of the cargoes, sense of personnel safety duty, and seasonal route, which are all key risk factors. Relevant management should take effective measures in advance according to these risk factors to avoid the incidence of transport accidents and should comprehensively elevate the safety level of deep-sea transport.

The five key risk factors identified in this study are generally consistent with the findings of existing maritime safety studies regarding dangerous goods leakage, hazardous

cargo properties, human factors, safety management, and emergency response. Specifically, risk of leakage reflects the direct accident risk caused by failures of cargo containment systems, packaging and sealing devices, or loading and unloading operations during dangerous goods transportation, which is an important trigger for secondary accidents such as fire, explosion, poisoning, and environmental pollution. Emergency speed reflects the efficiency of shipboard and shore-based support systems in responding to emergencies after an accident occurs, directly affecting whether risks can be controlled at an early stage and whether accident consequences will further expand. Physical and chemical properties of the cargoes represent the inherent hazardous characteristics of transported goods, such as flammability, explosiveness, toxicity, corrosiveness, volatility, and reactivity, and constitute a fundamental factor determining accident severity and risk propagation pathways. Sense of personnel safety duty represents the subjective willingness and behavioral constraint ability of crew members and relevant operators to comply with safety procedures, actively identify risks, and fulfill their safety responsibilities, serving as an important barrier against human errors and violations. Seasonal route reflects the adaptability of deep-sea transportation to seasonal environmental conditions, such as wind, waves, currents, visibility, typhoons, and sea ice, and indicates the management relationship between route decision-making and environmental risk avoidance. Together, these five factors form a complete risk evolution chain from hazard identification, route prevention, personnel execution, and accident triggering to emergency control, indicating that deep-sea transportation safety does not depend on a single technical factor, but rather on the coordinated interaction among cargo hazards, personnel behavior, environmental conditions, and organizational management barriers.

5. Discussion

In this section, the feasibility and effectiveness of the model proposed in this study are verified from three perspectives: sensitivity analysis, the time complexity of the algorithm, and the accuracy of the key factor identification results in Case C.

5.1. Parameter Sensitivity Analysis

To further verify the stability and robustness of the proposed model, this section conducts a sensitivity analysis of indicator weights. Since changes in evaluation indicator weights may affect the comprehensive ranking results of key risk factors, Case C is taken as the research object in this study. A single-factor perturbation analysis is performed on the weights of the six importance evaluation indicators of the risk factor, with variation levels of −20%, −10%, 0, 10%, and 20%, respectively, and the changes in the ranking results of the top five key risk factors are observed. The specific sensitivity analysis results are shown in Table 8.

It can be seen from the table that, when the weights of each evaluation indicator are varied by −20%, −10%, 0, 10%, and 20%, respectively, the top five factors in the comprehensive ranking are consistently composed of the five risk factors e29, e33, e26, e2, and e22. No new risk factor enters the top five, and none of the original top five factors drops out. This indicates that the constructed AHP-TOPSIS-GRA comprehensive evaluation results exhibit good stability and robustness, and that the identification of key risk factors is not fundamentally affected by slight changes in the weight of a single indicator. In particular, e29 consistently remains in first place, which further verifies the reliability of the comprehensive evaluation model. Meanwhile, local ranking changes mainly occur among e33, e26, e2, and e22, suggesting that the model results do not completely depend on a fixed set of weights. The set of key risk factors remains stable under weight perturbations,

further demonstrating the applicability of the AHP-TOPSIS-GRA method for identifying key safety risk factors in deep-sea transportation.

Table 8. Results of sensitivity analysis.

Parameter \ Rate of Change	−20%	−10%	0	10%	20%
Self-risk intensity	e29	e29	e29	e29	e29
	e33	e33	e33	e26	e26
	e26	e26	e26	e33	e33
	e2	e2	e2	e2	e2
	e22	e22	e22	e22	e22
In-risk intensity	e29	e29	e29	e29	e29
	e33	e33	e33	e33	e33
	e26	e26	e26	e26	e26
	e2	e2	e2	e2	e2
	e22	e22	e22	e22	e22
Out-risk intensity	e29	e29	e29	e29	e29
	e26	e26	e33	e33	e33
	e33	e33	e26	e26	e26
	e2	e2	e2	e2	e2
	e22	e22	e22	e22	e22
Weighted clustering coefficient	e29	e29	e29	e29	e29
	e33	e33	e33	e26	e26
	e26	e26	e26	e2	e2
	e2	e2	e2	e33	e22
	e22	e22	e22	e22	e33
Betweenness centrality	e29	e29	e29	e29	e29
	e2	e26	e33	e33	e33
	e26	e2	e26	e26	e26
	e22	e33	e2	e2	e2
	e33	e22	e22	e22	e22
Proximity	e29	e29	e29	e29	e29
	e33	e33	e33	e33	e33
	e26	e26	e26	e26	e26
	e2	e2	e2	e2	e2
	e22	e22	e22	e22	e22

5.2. Computational Complexity Analysis

Time complexity represents a crucial metric for assessing algorithmic effectiveness [49]. To verify the feasibility and effectiveness of the proposed method in terms of operational efficiency, this section discusses the time complexity of the proposed method. In this paper, the whole process of identifying the key risk factors affecting the safety of deep-sea transportation mainly includes two parts: the weight calculation of the indicator for importance assessment and the evaluation of node importance. Furthermore, the time complexity associated with the algorithm is analyzed using these two parts. n and m respectively represent the quantity of network nodes and the number of evaluation indicators. Firstly, six evaluation indices of node importance are established, and the evaluation matrix is calculated for each evaluation index. The time complexity measure of each index algorithm is $O(n^2)$. Then, the AHP method is employed to determine the weight assigned to each evaluation index, and the time complexity of this part is $O(m)$. Finally, the node importance is comprehensively evaluated based on TOPSIS-GRA, and the computational complexity of the algorithm is $O(n \times m)$. Accordingly, the time complexity

measure corresponding to the whole algorithm is $O(m \times n^2 + m + n \times m)$, which proves that this method enables the identification of influential nodes in large-scale networks within a constrained time frame.

5.3. Method Validity Verification

To demonstrate the effectiveness and advantages of the proposed AHP-TOPSIS-GRA framework, node topological criticality method is adopted as a benchmark node-ranking method in this study. Node topological criticality evaluates the importance of a node by measuring its contribution to the global efficiency and structural stability of the network [50]. Therefore, it can be used as a conventional network-based ranking method for comparison with the proposed framework.

The global efficiency E_{glob} is formulated in Equation (22) [51]. Combined with the characteristics of the risk factors exerting influence on the safety of deep-sea transportation, the quantitative formula of the topological criticality of the node TC_i is established by considering the influence of the node's risk intensity on the network (Equation (23)). The larger the topological criticality of a node, the greater the effect on the global efficiency of the network.

$$E_{glob} = \frac{1}{n(n-1)} \sum_{i \neq j}^{n} \frac{1}{d_{ij}} \tag{22}$$

$$TC_i = \frac{E_{glob}(n) - E_{glob}(n-1)}{E_{glob}(n)} \cdot R_i \tag{23}$$

where n represents the total number of nodes in the network, d_{ij} refers to the shortest path joining nodes i and j, E_{glob} and $E_{glob}(n-1)$, respectively, denote the network global efficiency in the presence and absence of node i, TC_i is the topological criticality of node i, and R_i represents the self-risk centrality of node i.

The topological critical values are calculated using Equations (22) and (23), and the topological critical values of the nodes are ordered from largest to smallest. Table 9 reports the corresponding results obtained from the calculations.

Table 9. Node topological criticality ranking.

Factors	TC_i	Ranking	Factors	TC_i	Ranking
e1	0.0006	20	e18	0.0019	12
e2	0.0047	3	e19	0.0011	17
e3	0.0021	10	e20	0.0016	14
e4	0.0021	11	e21	0.0011	18
e5	0.0021	9	e22	0.0041	4
e6	0.0000	34	e23	0.0005	23
e7	0.0001	30	e24	0.0019	13
e8	0.0001	31	e25	0.0024	7
e9	0.0002	26	e26	0.0109	2
e10	0.0002	28	e27	0.0037	5
e11	0.0006	21	e28	0.0022	8
e12	0.0012	16	e29	0.0217	1
e13	0.0006	22	e30	0.0013	15
e14	0.0002	27	e31	0.0006	19
e15	0.0001	29	e32	0.0005	24
e16	0.0004	25	e33	0.0035	6
e17	0.0000	33	e34	0.0001	32

In Table 9, the top five nodes are e29 (risk of leakage), e26 (physical and chemical properties of the cargoes), e2 (sense of personnel safety duty), e22 (seasonal route) and

e27 (comprehensiveness of the logo and sign) in the node topology critical value. The critical nodes determined on the basis of the node topology critical value are compared with the key nodes identified through the model constructed in the present study, as shown in Table 10.

Table 10. Statistical ranking table of key factors affecting deep-sea transportation safety.

Node Topological Criticality Ranking	Node Importance Ranking
e29	e29
e26	e33 (emergency speed)
e2	e26
e22	e2
e27 (comprehensiveness of the logo and sign)	e22

According to the analysis in Table 10, the key nodes identified using the model are basically in agreement with the key nodes from the ranking using the node critical value, which confirms the effectiveness of the method constructed in this study. In addition, there are some limitations in quantifying the contribution attributable to nodes to the global efficiency of the network when using the topological critical value [50]; when combined with the characteristics of the deep-sea location, which is usually far from the coast, deep-sea accidents place higher requirements on rescue response speed. Therefore, it is more reasonable and realistic to identify node e33 (emergency speed) as the key node using the model in this paper. The analysis of the actual situation further validates the effectiveness of the proposed model and the accuracy of the identification results of key factors.

6. Conclusions

To effectively identify key risk factors in deep-sea transportation, this study introduces complex network theory, the AHP method, the TOPSIS method, and the GRA method into the field of deep-sea transportation safety and constructs a key risk factor identification model. The feasibility and effectiveness of the proposed model are verified through a representative case study, indicating that the model can provide strong support for ensuring deep-sea transportation safety.

Based on the five key risk factors identified using the proposed model, this study further proposes the following control measures, so as to help maritime authorities, shipping companies, and safety managers formulate effective prevention, control, and response strategies for different types of risks, prevent deep-sea transportation accidents, and comprehensively improve the safety level of deep-sea transportation.

In terms of leakage risk, maritime administrations should strengthen the supervision of dangerous goods transportation and require shipping companies to strictly comply with relevant regulations, such as the IMDG Code. Shipping companies should use qualified cargo tanks, containers, packaging materials, and sealing devices, and conduct leakage inspections before loading, during transportation, and before unloading. Emergency leakage-control equipment, such as absorbent materials, plugging tools, protective equipment, and fire-fighting devices, should also be equipped on board.

In terms of emergency speed, shipping companies should establish deep-sea emergency response plans covering scenarios such as fire, leakage, collision, grounding, and personnel injury. Emergency equipment and rescue materials should be arranged in advance, and crew members should regularly participate in emergency drills. Maritime administrations can improve ship–shore emergency communication mechanisms and require vessels operating on deep-sea routes to report their emergency response capability before departure.

In terms of physical and chemical properties of the cargoes, shipping companies should strictly verify cargo properties before shipment, including flammability, explosiveness, toxicity, corrosiveness, volatility, and reactivity. Cargo safety data sheets, transport documents, hazard labels, and emergency handling instructions should be complete and accurate. Incompatible cargoes should be properly segregated, and cargoes sensitive to temperature, humidity, or vibration should be monitored during transportation.

In terms of sense of personnel safety duty, shipping companies should strengthen safety responsibility education for crew members and clarify the safety duties of each position. Regular training and assessment should be conducted on safe operation, emergency response, dangerous goods handling, and accident reporting. A responsibility-based safety management system should be established to ensure that crew members strictly follow operating procedures during deep-sea transportation.

In terms of seasonal route, maritime administrations and shipping companies should optimize route planning according to seasonal changes in wind, waves, currents, visibility, typhoons, and sea ice. Before departure, vessels should conduct seasonal navigation risk assessments and formulate alternative routes. During navigation, weather routing, real-time meteorological monitoring, and early-warning information should be used to avoid high-risk sea areas and periods.

However, due to the limitations of the authors' research capacity, there are still some shortcomings in this study that need to be further improved in future research. Firstly, the risk factor network constructed in this paper is a static network, which mainly reflects the relationships among risk factors under specific case conditions. However, in actual deep-sea transportation, risk factors may change dynamically with navigation time, seasonal sea conditions, cargo status, vessel operating conditions, and emergency response processes. Secondly, due to the limited availability of probabilistic accident data for deep-sea transportation, the construction of the risk factor network, the determination of risk state values, the assignment of edge weights, and the determination of the weights of node importance evaluation indicators still rely, to some extent, on expert judgment. Therefore, the evaluation results may contain a certain degree of subjectivity, as well as regional or institutional bias. Specifically, the professional background, practical experience, institutional affiliation, and familiarity of the participating experts with different transportation scenarios may influence their judgments regarding the importance of risk factors and the causal relationships among them. On the one hand, uncertainty in risk state values may affect self-risk centrality, while uncertainty in directed edge weights may affect network-based evaluation indicators such as in-risk strength, out-risk strength, the weighted clustering coefficient, betweenness centrality, and closeness centrality. These changes may be further transmitted to the TOPSIS-GRA comprehensive evaluation process and may ultimately affect the closeness values and ranking results of risk factors. On the other hand, uncertainty in the weights of node importance evaluation indicators may also influence the ranking results. As a consequence, in order to reduce the influence of subjectivity in expert judgment on the evaluation results, this study adopted feedback revision and consistency testing during the expert scoring process to reconfirm scoring results with large discrepancies. In addition, sensitivity analysis was conducted to examine the influence of changes in the weights of evaluation indicators on the identification results of key risk factors. The results show that, when the weights of the evaluation indicators are changed within a certain range, the top five key risk factors remain stable, indicating that the identification results of this study have a certain degree of robustness. Therefore, when the proposed framework is applied to other deep-sea routes or fleets, the model structure can be transferred and used; however, the relationships among different risk factors, their influence strengths, and the risk state

values of each risk factor should still be recalibrated according to the specific navigation environment, cargo type, vessel characteristics, and management conditions.

In future research, dynamic and data-driven elements can be incorporated into the network model. For example, time-varying data such as AIS data, meteorological and oceanographic data, cargo monitoring data, vessel equipment status data, accident reports, and near-miss records can be used to dynamically update node states and edge weights. In addition, probabilistic models, Bayesian networks, machine learning methods, or dynamic complex network models can be introduced to describe the evolution process of risk factors and improve the objectivity and predictive capability of key risk factor identification.

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