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A Bayesian network based framework for ripple effect analysis in cross-tier shipbuilding supply chains

Yiqi Zhang, Yanhui Ma, Le Wang *, Zhiqiong Wang, Lixia Zhang

School of Management, Tianjin University of Technology, China

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ABSTRACT

Modern shipbuilding supply chains are increasingly vulnerable to cascading risks across multiple tiers. However, existing analytical models fail to adequately capture the nonlinear propagation of disruptions due to over-simplified dependency mappings and the neglect of latent risks. This limitation impairs managers' ability to effectively manage ripple effects within multi-level production systems. This study proposes a Bayesian network (BN) with a leaky noisy-or to evaluate disruption propagation and resilience in both multi-level cross-tier and single-level linear shipbuilding supply chains. The framework models bidirectional dependencies and latent risks, quantifying how cross-tier structures leverage redundant pathways to mitigate downstream disruptions. Additionally, it identifies critical nodes and evaluates disruption scenarios through probabilistic analysis of interdependency. To validate the proposed framework, we conducted a 23-node shipbuilding supply network based on the operations data of J-shipyard. This work comparatively analyzes between cross-tier BN structures and conventional linear network representations. The cross-tier network demonstrated superior performance reducing downstream disruptions by 10.3%, thereby highlighting the resilience advantages of alternative pathways. Sensitivity analysis revealed that raw material suppliers are critical vulnerabilities, as indicated by a sensitivity index exceeding 0.25. This research advances the field of disruption analysis in complex production systems by enabling precise risk prioritization and optimizing pathway redundancy. Practitioners can utilize this framework to enhance the resilience of tiered supply chains, particularly in industries characterized by complex supply chains. The adaptability allows for its application across various multi-level organizations.

1. Introduction

The shipbuilding industry is a cornerstone of global trade and advanced manufacturing. Characterized by long production cycles, international specialization, and limited connectivity across all tiers, the shipbuilding supply network is particularly vulnerable to ripple effect. The ripple effect refers to a phenomenon whereby a minor disruption within a system triggers larger impacts as it propagates across interconnected nodes (Ivanov et al., 2014). China's dominance in the industry, evidenced by 50.2 % of global shipbuilding completions and 66.6 % of new orders in 2023,[1] highlights its strategic significance. Nonetheless, systemic weaknesses continue. Incidents such as the Ningbo-Zhoushan port collision in 2020 illustrates how localized technical or operational failures can trigger multi-level crises, emphasizing the nonlinear nature of disruption propagation.

While prior studies have advanced the analysis of supply chain disruptions, three key limitations persist. First, existing models oversimplify unidirectional risk flows and overlook the inherent bidirectional dependencies that characterize vertically integrated industries (Babaleye et al., 2019; Hosseini et al., 2022). Second, modeling multilevel systems faces excessive computational complexity, leading to over-simplified representations (Liu et al., 2021a). Third, ripple effects of disruption propagation remain insufficiently addressed in many existing approaches. These issues are particularly evident in the shipbuilding industry, where the close connections between raw material suppliers, modularization factories, and assembly plants create complex pathways for the transmission of risk.

Against this backdrop, this study proposes a Bayesian Network integrated with a leaky noisy-or to handle bidirectional causal decomposition of interactions across supply chain tiers. The framework quantifies latent risks using Gaussian-distributed leakage probabilities, optimizes cross-tier redundancy through probabilistic interdependency analysis,

* Corresponding author.
E-mail address: le_wang@email.tjut.edu.cn (L. Wang).

[1] https://www.gov.cn/lianbo/bumen/202401/content_6926420.htm.

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and supports scenario-based evaluation based on empirical data for proactive risk mitigation. It aims to clarify how bidirectional hierarchical node dependencies alter risk propagation paths and intensities, verify whether the leaky noisy-or can effectively account for the impact of unobserved risks on outage probabilities, and determine if cross-tier redundant pathways mitigate ripple effects. Ultimately, it provides a method for precise risk prioritization and enhancing resilience in cross-tier shipbuilding supply chains. To systematically solve the above problems, this study takes a modeling to quantify the optimization framework and formulates the following three verifiable research questions:

RQ1: How do bidirectional cross-tier dependencies influence disruption propagation paths in comparison to those in single-level linear structures?
RQ2: Can leaky noisy-or models effectively capture the contribution of unobserved risk to outage probability?
RQ3: Do redundant cross-tier pathways significantly mitigate ripple effects across hierarchical supply chain structures?

This study addresses the existing gaps from three dimensions by constructing an analysis framework for ripple effects in cross-tier shipbuilding supply chains:

(1) **Management contributions:** This study quantifies the risk mitigation effects of redundant pathways, demonstrating a 10.3 % reduction in downstream disruption probability. The findings enable network architecture optimization through direct cross-tier connections (e.g., A1 to C1) and dual-path supply models. Sensitivity analysis reveals critical vulnerabilities in raw material suppliers, guiding prioritization of supplier diversification and strategic inventory. A leakage probability shipyard risk correlation is established, supporting a proactive risk framework with quarterly scenario simulations to anticipate extreme events and reserve contingency resources.
(2) **Methodological contributions:** This study provides develop a bidirectional Bayesian network integrated with leaky noisy-or that enables comprehensive disruption analysis. The framework simulates forward propagation of material shortages through component delays to shipyard shutdowns, while backward diagnosis traces shipyard demand fluctuations to upstream inventory backlogs. Cross-tier collaborative mitigation is facilitated through alternative pathway activation (e.g., B2 to D2 bypassing C2 disruption) and root-cause identification via backward reasoning (e.g., inferring A3, B3 joint impact from C4), optimizing emergency resource allocation.
(3) **Theoretical contributions:** This work establishes a bidirectional dependency theory, revealing cross-tier pathways account for 28 % to 45 % of total risk transmission—challenging conventional unidirectional risk paradigms. The structural redundancy principle demonstrates how cross-tier hubs (e.g., A5 to C5 to E) disperse single-path risk through hierarchical interdependence. By integrating leakage probability into supplier evaluation (e.g., requiring latent risk response plans for critical nodes like B1), we advance latent risk quantification theory, shifting decision-making from known-risk control to unknown-risk anticipation.

This study applies the proposed framework to J Shipyard's real-world multi-level cross-tier supply chain and validates its effectiveness in quantifying and mitigating disruptions via numerical experiments. Results show cross-tier networks reduce disruption propagation probability by over 10 % versus linear structures, with raw material suppliers most vulnerable. The research benefits shipbuilding and offers a reality-based analytical method for aerospace, automobile manufacturing, etc., with multiple dependencies and extended production cycles.

The subsequent sections of this paper are organized as follows: Section 2 provides a review of the existing literature related to ripple effects, disruptions in supply chains, and the applications of the Bayesian Network (BN). Section 3 describes the gaps of existing research and the main contributions of this study. Section 4 delineates the design of the framework, which includes structural mapping, probabilistic modeling, and the execution of numerical experiments. Section 5 presents the results of the numerical experiment, and Section 6 offers findings and implications for management. Section 7 discusses the conclusions and the limitations of this study and suggests avenues for future research.

2. Literature review

This section provides a comprehensive review of research advancements in supply chain disruption analysis, including ripple effects and the Bayesian network. These topics will help us understand the complexities and usefulness of the Bayesian network in analyzing supply chain disruptions, setting the stage for future theoretical research and real-world applications.

2.1. Shipbuilding supply chain disruption analysis

As the global trade expanding and supply chain managements becoming increasingly complex, the shipbuilding industry is characterized by intricate and large-scale equipment manufacturing processes. The associated supply chain networks exhibit a high degree of complexity, which has attracted considerable attention from both academic and industrial sectors. Given the complexity inherent in shipbuilding supply chains, researchers have studied the spread of disruptions to improve efficiency, stability, and sustainability (Ferreira et al., 2018; Yang et al., 2023). Sahin et al. (2021) created an enhanced game-theoretic model using the Improved Fuzzy Analytic Hierarchy Process (IFAHP) to compare shipyard risks and determine the optimal shipyard selection under different conditions. Meng et al. (2023) used other methods and the set pair analysis-Markov chain model to assess and predict the risk of cruise shipbuilding supply chain. This evaluation system provided both theoretical and empirical support for preventing disruptions. Li et al. (2023) used a directed network model to identify single and multiple shipbuilding supply chain risks, explored interconnections, and provided a new perspective for developing strategies to prevent and manage disruptions. It is essential for global sustainable development. Sezer et al. (2023) examined the causes and effects of ship cabin failure using a robust bow-tie risk analysis method within the D-S-HEART framework. In a similar vein, Durukan et al. (2024) simulated tanker ship failures and assessed fire and explosion risk based on fault scenarios. Meanwhile, Liu et al. (2024) proposed a specific network to study how disruptions propagate, including their probabilities and mechanisms.

This research has helped our understanding of disruption propagation at single levels and informed local mitigation strategies. However, two major issues persist. First, most models only consider unidirectional risk along straight liners, failing to reflect the bidirectional dynamic between upstream suppliers and downstream suppliers in shipbuilding. Second, traditional approaches, such as the fuzzy analytic hierarchy process, rely on fixed risk assessment systems that cannot account for how disruption propagates as conditions change. These challenges underscore the need to examine inter-tier interactions from both structural and behavioral perspectives.

2.2. Ripple effect

The ripple effect occurs when suppliers and manufacturers are unable to manage local disruptions. These localized failures spread throughout the supply chain. It may lead to the collapse of supply network nodes or connections. It can also alter supply chain structures and ecosystems, resulting in severe consequences for the global economy (Abimbola, Khan, Khakzad, & Butt, 2015; Hosseini et al., 2019;

Ivanov, 2017; Ivanov, Dolgui, & Sokolov, 2019; Ivanov, Sokolov, & Dolgui, 2014; Kinra, Ivanov, Das, & Dolgui, 2020; Özçelik, Faruk Yılmaz, & Betül Yeni, 2021; Sokolov, Ivanov, Dolgui, & Pavlov, 2016). Existing research have developed link-based models to better understand these effects. Ivanov et al. (2015) created a ripple effect-based control system. This system uses mathematical models to enhance supply chain resilience and planning. Sokolov et al. (2016) used static and dynamic control models to study the structural ripple effects in supply chain. Sawik (2019) developed a two-stage decision-making method to mitigate and recover from ripple effect supply disruptions. Ojha et al. (2018) developed a Bayesian network for supply chain risk propagation. They evaluated node disruptions using ripple effect metrics such as vulnerability, service levels, inventory costs, and lost sales. Hossain et al. (2020) proposed a mathematical model for supplier selection that considered the ripple effect. Dolgui et al. (2020) and Li et al. (2021) developed agent-based computing models to simulate how supply chain topology influences disrupt propagation. Dubey et al. (2021) linked resilience capabilities with data analysis to visualize ripple effects. Yılmaz et al. (2021) designed sustainable reverse supply chains under ripple effects. They used a two-stage stochastic optimization model to estimate the increase in total cost caused by ripple effects. Sindhwani et al. (2023) combined Bayesian Networks and rational planning. Their framework links mitigation capability to network design properties. Alam et al. (2024) modeled the systemic interrelationships among the contributing factors to address the ripple effect of food supply chains in emerging economies such as Bangladesh. Zhang et al. (2024) suggested a mixed ripple effect model with four types of failures to explain how disruptions spread in different situations, whether alone or in combination. Yılmaz et al. (2023) emphasized that the traditional supply chain faces the risk of disruption due to the ripple effect and unknowable uncertainty. Yeni et al. (2025) integrated the stochastic programming model into the continuous improvement cycle. And a comprehensive approach equipped with lean tools is proposed to address the risks caused by the chain reaction. Yılmaz et al. (2025) balance the advantages of stochastic programming and robust optimization through a unified robust stochastic programming model to address known and unknown demand uncertainties and ripple effects in complex high-risk environments. Hosseini et al. (2019), Hosseini et al. (2020) and Liu et al. (2021a) utilize quantified risk impacts to analyze the ripple effects systematically within the supply chain during the pandemic. Liu et al. (2021b) studied integrated supplier selection and disruption risk minimization under chain reactions. Brusset et al. (2023), Sawik (2025), and Yılmaz et al. (2025b) suggested quantifying risk through risk-averse decisions to reduce ripple effects. Yılmaz et al. (2025) used supply chains to quantify the impact of uncertainty quantification ripple effects on supply chain resilience in known-unknown scenarios and unknown-unknown scenarios. All previous studies either predicted effects using data and modeling probabilities, interpreted linkages or quantified them.

While these studies provide valuable insights, most assume unidirectional propagation, typically from upstream to downstream. This assumption neglects bidirectional feedback loops that frequently occur in vertically integrated industries like shipbuilding. Additionally, many models rely on simplified topologies (e.g., tree structures), which do not represent redundant cross-tier connections or feedback mechanisms. These limitations restrict the applicability of traditional ripple effect models to complex industrial systems. Therefore, a new analytical framework is required to capture multi-directional and nonlinear disruption propagation across interdependent tiers.

2.3. Application of Bayesian networks in supply chain disruptions

The Bayesian network is widely used for analyzing disruption propagation across supply chains due to their ability to model complex causal relationships (Garvey et al., 2015; Hosseini et al., 2020). Recent studies demonstrate their effectiveness in capturing cross-tier risk propagation mechanisms. Käki et al. (2015) utilized the BN to quantify how supplier disruptions propagate across multi-level networks. These findings highlighted the amplified impact of single-node failures in hierarchical structures. Zhou et al. (2016) used the BN to examine the consequence of disruptions at inland nodes. Their model captured both upstream and downstream these problems occur, demonstrating that disruptions can spread. The potential risk of the chain reaction that may be caused by a high degree of severe disaster can be effectively solved by risk avoidance (Yılmaz et al., 2025a). Hosseini et al. (2020) suggested using the noisy-or method to mitigate computational complexity and address exponential parameter growth.

Henrion (1988) proposed that it is necessary to consider that not all fault conditions can be considered when establishing the Bayesian network in practical applications. Specifically, even in the absence of the identified cause, a node may still fail. Therefore, the concept of missing probability needs to be introduced. Leakage probability refers to the probability that unconsidered risk factors (such as geopolitical and natural disasters) will directly cause a node to fail. Basnet et al. (2023) and Nicknezhad et al. (2024) used the BN with a noisy-or model to study how different parts of port and multi-level supply chains are connected. Chen et al. (2024) used a leaky noisy-or model to examine hidden issues in systems that operate at different levels, including additional factors to account for unseen risks (such as geopolitical shocks) that could exacerbate problems worse across those levels. Feng et al. (2020) and Liu et al. (2023) used the BN and a leaky noisy-or to study complicated paths of disruptions in gas pipelines and tools, which helps in examining supply networks in maritime transport that operate at different levels.

The Bayesian Network has been widely validated for modeling supply chain risk propagation. However, there are two limitations. First, the traditional BN model is limited to single-level causal chains and cannot characterize cross-tier joint effects. Second, existing improved methods such as the noisy-or model mainly deal with explicit dependencies, overlooking latent or unobserved risks. This work improves the analysis of ripple effects in shipbuilding supply chains by introducing a two-way dependence path and a Gaussian distribution leakage parameter. Meanwhile, it broadens the application scenario of the Bayesian network and measures the propagation of disruptions across the shipbuilding supply chain hierarchy.

3. Research gaps and contributions

Table 1 systematically demonstrates the comparison of existing studies with this research across five dimensions, highlighting critical gaps in traditional approaches and the innovations introduced in this study. First, in cross-tier modeling, most existing studies focus on single-level linear supply chains, overlooking direct interactions between cross-tier nodes. For example, control models (Ivanov et al., 2015) force meshed supply chains into tree topologies, ignoring cross-tier redundant paths, while dynamic Bayesian networks (Hosseini et al., 2020; Liu et al., 2021a) simplify supply chain networks to two-tier networks with three nodes. Second, regarding ripple effect analysis, traditional methods assume unidirectional risk flow, failing to capture bidirectional feedback. Most of studies (Ojha et al., 2018; Li et al., 2021) overlook reverse propagation and cross-tier jumps. At the same time, the ripple effect of intermediate nodes upstream and downstream is not considered. Third, for implicit risk quantification, conventional models neglect unobserved factors. Potential factor analysis is mainly reflected in system failure analysis. In existing supply chain disruption analysis, the influence of potential factors is often ignored. Fourth, in probability analysis, existing methods rely on static or a fuzzy logic, lacking dynamic causal reasoning. Although Ferreira et al. (2018) proposed fuzzy AHP model that fails to update node dependencies. The dynamic Bayesian network (Hosseini et al., 2020) introduces the time dimension, and the hierarchical isolation hypothesis makes it unable to express cross-tier causal relationships. In summary, existing methods suffer from topological oversimplification, unidirectional analysis, and the neglect

Table 1
Summary of the Reviewed Literature.

	Cross-tier	Ripple Effect	Implicit Risk	Probability Analysis	Disruption Analysis Method
Ivanov et al., 2015		√			Control Model (Mathematical Programming)
Sokolov et al., 2016		√			Structural Dynamic Control Model
Ferreira et al., 2018				√	Game Theory; Fuzzy Analytic Hierarchy Process
Ojha et al., 2018		√		√	Bayesian Network
Sawik, 2019		√			Two-stage Decision Model
Hossain et al., 2020		√			Dynamic Bayesian Network
Liu et al., 2021a		√		√	Dynamic Bayesian Network
Feng et al., 2020			√	√	Bayesian Network; Leaky Noisy-OR Model
Li et al., 2021		√			Complex Network
Dubey et al., 2021		√			Data Analysis
Yılmaz et al., 2021					Stochastic Mixed-integer Optimization Model
Hosseini et al., 2022		√		√	Bayesian Network
Sindhwani et al., 2023		√		√	Bayesian Network; Rational Planning
Meng et al., 2023				√	Bayesian Network; Leaky Noisy-OR Model
Yılmaz et al., 2023					Rational planning; lean tools
Sezer et al., 2023				√	Dempster-Shafer evidence theory
Liu et al., 2023			√	√	Bayesian Network ; Leaky Noisy-OR Model
Durukan et al., 2024		√		√	Dempster-Shafer evidence theory; Fault Tree Analysis
Chen et al., 2024			√	√	Bayesian Network; Leaky Noisy-OR Model
Nicknezhad et al., 2024				√	Bayesian Network; Leaky Noisy-OR Model
Sawik, 2025				√	Stochastic Mixed-integer Optimization Model
Yılma et al., 2025a		√			Rational planning; Machine Learning
Yeni et al., 2025					Rational planning; lean tools
This study	√	√	√	√	Bayesian Network ; Leaky Noisy-OR Model

of implicit risk. This research addresses these issues through a three-dimensional framework with cross-tier structure model, latent risk quantification, and bidirectional dependency analysis—bridging the gap between traditional linear models and the complex reality of vertically integrated supply chains.

Hosseini et al. (2020) provided an important basis for dynamic models of supply chain disruptions, serving as this research's benchmark. Their dynamic Bayesian network (DBN) model, combining Markov chain, first quantified unidirectional upstream disruption propagation in single-level supply chains. However, it has limitations in multi-level causal chain modeling: focusing only on upstream–downstream one-way risk flow, ignoring vertical integration's bidirectional feedback; concentrating on single-level risk propagation, neglecting cross-level interactions; and excluding unobserved factors (e.g., geopolitical shocks), leading to poor interpretation of complex disruptions. Existing studies generally assume one-way risk flows, overlook bidirectional dependencies, face computational complexity in multi-level systems, and lack in-depth research on ripple effects.

The bidirectional causal decomposition accurately reflects supply chain bidirectional interactions, establishing cross-tier node links unaddressed in traditional studies. For scenario extension, the BN with a leaky noisy-or model are first applied to analyze cross-tier supply chain disruption propagation, quantifying observed and hidden risks for more comprehensive risk assessment. Its use in shipbuilding highlights identifying supply chain disruptions, involving pinpointing high-risk suppliers, exploring unknown variables, and developing measures to mitigate spread-induced risks.

4. Model building and analysis

4.1. Problem description

This study addresses the research gap by examining the levels and connections within maritime supply chains and how disruptions can impact others. The shipbuilding industry is selected as the case for the following rationale: (1) As the cornerstone of global advanced equipment manufacturing and international trade, the shipbuilding sector features inherently multilayered supply chains, extended production cycles, and deep globalization; (2) The industry demands exceptionally high product quality standard and frequently rely on single-source suppliers for critical components. It is essential to develop a method for analyzing how problems in the supply chain can spread, considering the complex structure and reliance on single supplier. This study proposes a novel framework, as illustrated in Fig. 1.

To illustrate the ripple effect in cross-tier shipbuilding supply chains, consider a simplified three-tier network with the following nodes:

Take the cross-tier dependence of raw material suppliers (A1), component manufacturers (B1) and shipyards (E) in the ship supply chain.

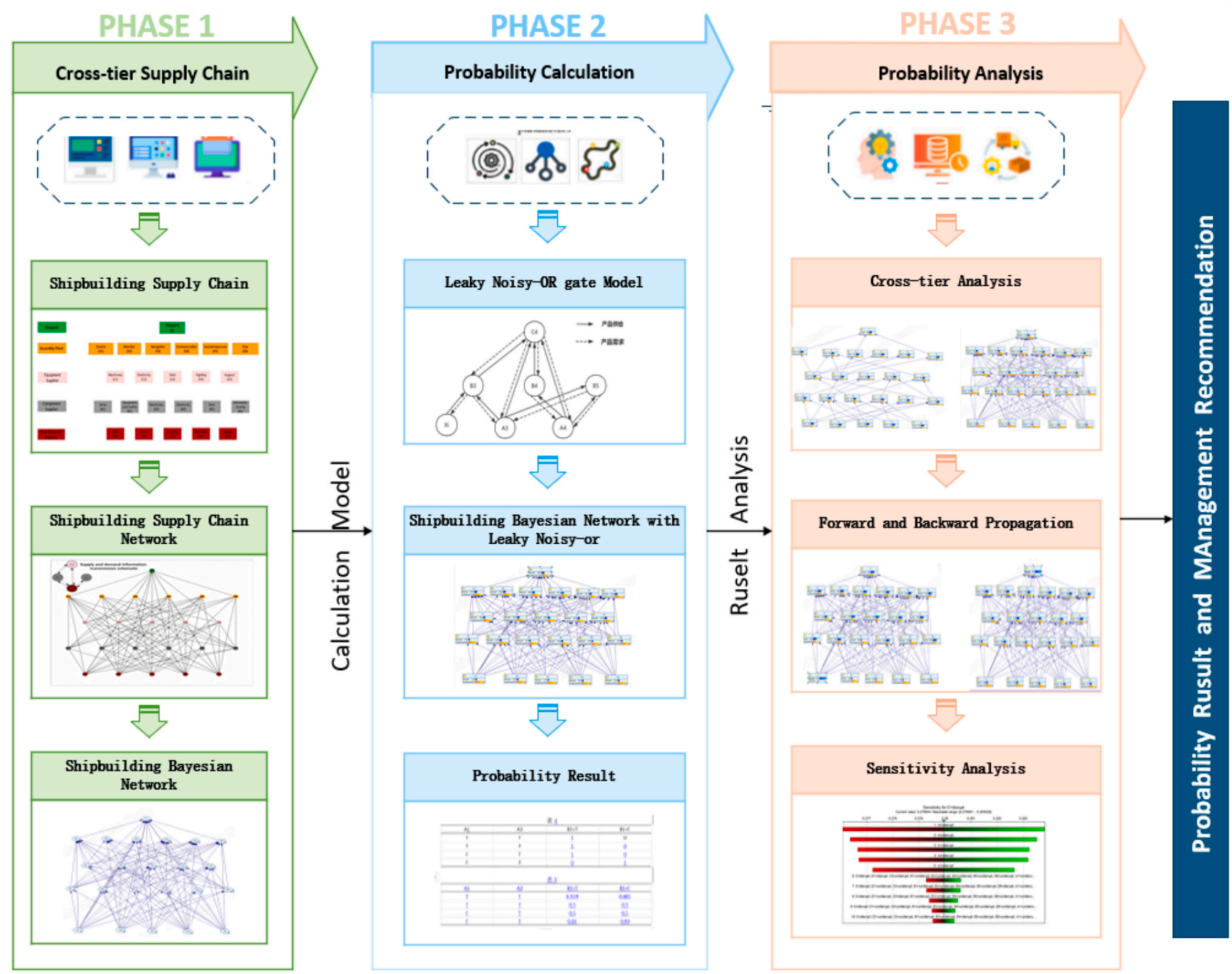


Fig. 1. Research Framework Diagram.

The traditional one-way model:

Assuming that only linear risk transmission paths A1 to B1 to E are considered, and the disruption probability of each node is assumed to be A1 = 14 % and B1 = 7 %. Then, the disruption probability of shipyard E is:

$P(E) = 1 - (1 - 0.14) \bullet (1 - 0.07) \approx 20\%$

The cross-tier Bayesian network model proposed in this paper:

Add the direct connection between A1 and C1. Assuming that the probability of disruption is 10 % of this path A1 to C1, the risk propagation path is extended to A1 to B1 to C1 to E and A1 to C1 to E. The leakage probability of a Gaussian distribution (e.g., leakage probability is 5 %) is introduced through the leaky noisy-or to quantify the independent impact of unobserved risks (e.g., port congestion) on nodes. In this case, the disruption probability of shipyard E is:

$P(E) = 1 - (1 - 0.14 \times 0.1) \bullet (1 - 0.07) \bullet (1 - 0.05) \approx 12.9\%$

Compared with the traditional model, the cross-tier structure reduces the probability of disruption of E by 7.1 %, highlighting the inhibitory effect of redundant paths on the ripple effect of disruption.

The proposed model encompasses end-to-end disruption modeling and analysis for shipbuilding supply chains. The issue being studied is tested using fake data based on real-world examples, and the network setup matches actual supply chain layouts. The Beta distribution is chosen for its flexibility in modeling probabilities within [0,1], which aligns with the bounded nature of disruption likelihoods. This study adopts the following assumptions:

(1) Supply chain connections represent the relationships product supply and demand.
(2) Cross-tier connections enable nodes to provide fungible goods to adjacent nodes.
(3) Goods provided by upstream, downstream, and cross-tier nodes are similar in nature but irreplaceable due to detailed differences in specifications, performance parameters, or integration requirements.
(4) To ensure stochastic realism in data generation, a Beta distribution with shape parameters $\alpha = 1$ and $\beta = 1$ is employed.
(5) The leakage probability follows a Gaussian distribution with a confidence of 99 % (Chen et al., 2024).

4.2. Framework for disruption analysis

This section presents a three-stage paradigm for assessing supply chain disruptions using cross-tier ripple effects (Fig. 1), with BN as the primary analytical tool. Fig. 1 depicts the first step in creating a BN of the marine supply chain, clearly showing how different levels depend on one another. In the second stage, a leaky noisy-or model is employed to quantify both observed and hidden risks, thereby avoiding oversimplified linear assumptions. The third step uses numerical experiments to validate how cross-tier connectivity mitigates disruptions.

The framework highlights a unique feature: bidirectional risk tracking. BN provides forward tracking, reverse diagnosis, and bidirectional propagation, revealing flaws in cross-tier dependencies.

4.3. Phase 1: Construction of the cross-tier shipbuilding supply chain

4.3.1. The composition of the shipbuilding supply chain

The shipbuilding supply chain is complex, beginning with the procurement of raw material to the delivery of products. This intricate chain comprises raw material suppliers, component manufacturers, assembly factories, distributors, and ancillary services, including financial, logistical, and technical support. The shipbuilding supply chain is organized hierarchically, with raw material providers, component suppliers, assembly companies, equipment suppliers, and shipyards. Fig. 2 depicts a five-level shipbuilding supply chain with multiple suppliers. They are raw material suppliers (e.g., steel, coatings), component suppliers (e.g., electrical equipment), block manufacturers (e.g., hull modules), system integrators (e.g., power systems), and shipyards (final assembly and delivery).

4.3.2. Multi-tier and cross-tier shipbuilding supply chain network

The shipbuilding supply chain network employs multi-party cooperation, resource integration, and process coordination. Nodes represent parts, modules, or products, and directed arcs show supply and demand. Cooperation between businesses that exchange information, materials, or capital forms network edges. Raw material suppliers serve shipyards, component manufacturers, equipment manufacturers, and sectional factories. Fig. 3 depicts the multi-tier and cross-tier supply chain network. Nodes are identified by letters and numbers. For example, nodes are hierarchical suppliers in Fig. 2, A1-A5 are raw material suppliers, B1-B6 are component manufacturers. The main diagram does not illustrate the circularity of supply and demand to simplify the network structure. Instead, the small diagram in Fig. 3, located in the top-left corners, elucidates bidirectional exchanges of supply–demand information, elucidating the fundamental logic of their interaction. To better clarify, the cooperative linkages in the main network are highlighted, with all lines bidirectional, as shown in the tiny diagram.

A Bayesian Network is constructed to model disruption propagation across cross-tier supply chains by capturing causal relationships among

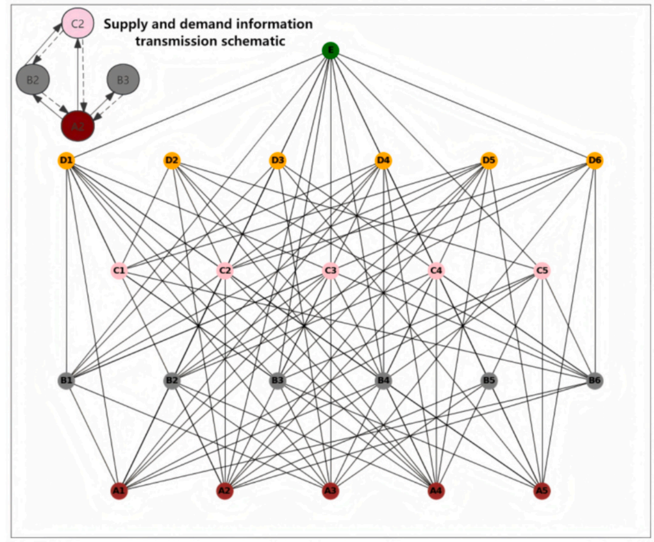


Fig. 3. Multi-tier and Cross-tier Supply Chain Network.

hierarchical nodes. Structural mapping and probability calculation are performed by GeNle Academic 4.1, which supports causal reasoning and sensitivity analysis of complex networks. Fig. 3 is mapped onto a BN and visualized in GeNle Academic 4.1 to facilitate understanding of the complex relationships within the supply chain network. However, due to its limitations, it can only do BN network mapping, as shown in Fig. 4. Nodes are represented as discrete variables, and directed edges represent causal dependencies.

4.4. Phase 2: Model of cross-tier shipbuilding supply chain disruption propagation

Fig. 5 shows a portion of the supply chain from Fig. 4, highlighting the connections and hidden risks between critical levels, which helps to reveal the main workings of the model in more detail. The construction logic is detailed below:

(1) Principles of subnetwork extraction and simplification

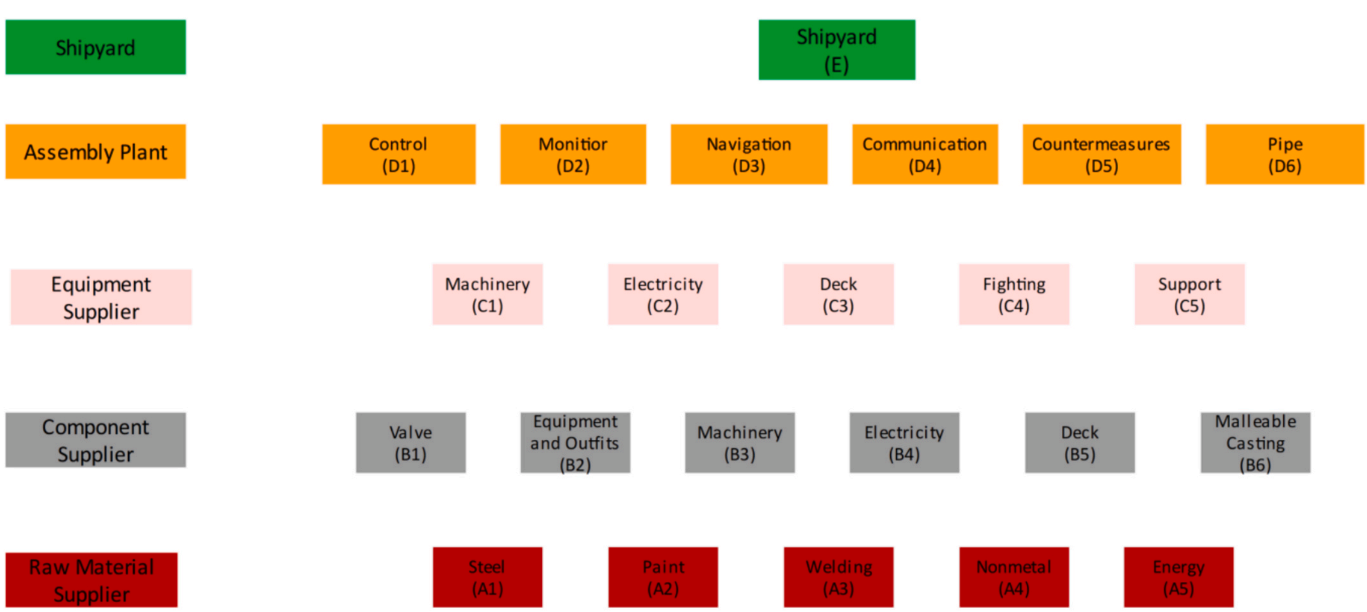


Fig. 2. Example of a Five-level Shipbuilding Supply Chain.

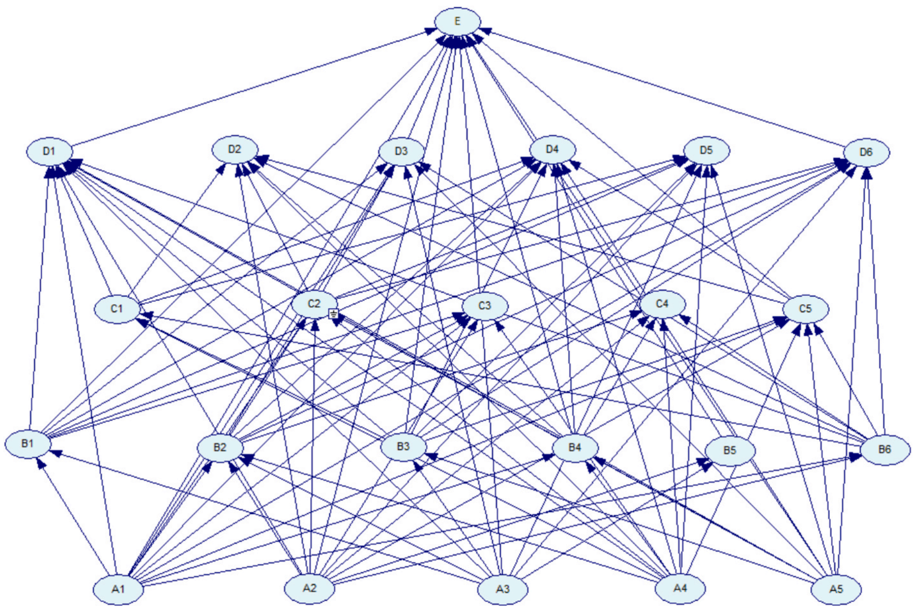


Fig. 4. Mapping of the Supply Chain to a Bayesian Network.

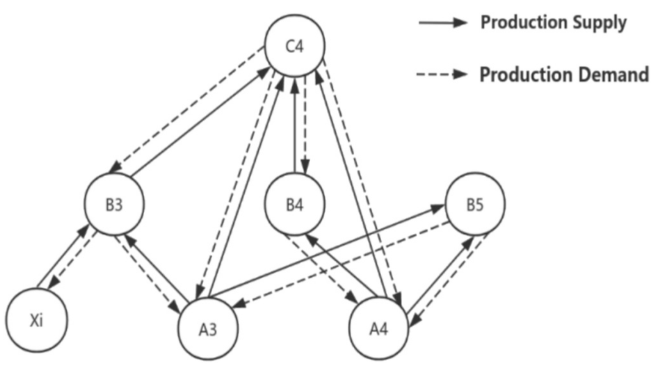


Fig. 5. Noisy-OR Model for Quantification of Cross-tier Disruption Propagation.

Take the full network topology of Fig. 4, extract the local structure containing core nodes such as C4, B3, and A3, their directly dependent paths in Fig. 5, and eliminate non-critical nodes to reduce complexity. For example, Fig. 5 shows how the production delay of component C4 is affected by its upstream nodes B3 and A3, and how it also affects the downstream nodes A4 and B4.

(2) Explicit modeling of leakage probability

The noisy-or model is used to assume that the parent node independently triggers the disruption of the child node. Let child node X have n parent nodes $Y_1, Y_2, \cdots, Y_n$, and the probability that each parent node Y_i alone will disrupt child node X is $P(X|Y_i = 1)$ ($Y_i = 1$ indicates that the parent node Y_i is disrupted), and the parent nodes are independent of each other. The calculation formula for the leaky noisy-or model is in Appendix A.

In Fig. 5, latent risk (e.g., natural disasters) is introduced independently through the leakage node Xi and combined with the dominant parent nodes B3, and A3 as trigger factors for the child node C4. The conditional probability formula is:

$P(C4 = 1|B3, A3, X_i) = 1-(1-p_{B3})\bullet(1-p_{leak})\bullet(1-p_{A3}\bullet p_{A3\rightarrow B3})$where p_{leak} is the probability of leakage, characterized by the direct impact of unobserved risk on C4. According to Chen et al., 2024 and Meng and Wu, 2023, the probability of leakage can obey a Gaussian distribution with a confidence of 99 %. This design makes up for the deficiency of traditional BN in modeling hidden factors. Part of the calculation results are shown in Appendix B.

(3) Visual splitting of bidirectional dependency path

Since BN only shows one-way cause-and-effect relationships, the two-way dependencies, such as levels A and C, are split into a forward path A3 to C4 and a backward inference path C4 to A3. The first path measures how disruptions move from the upstream to the downstream using the noisy-or model, while the second path shows how changes in downstream demand affect the upstream by updating probabilities.

4.5. Phase 3: Analysis of cross-tier shipbuilding supply chain disruption propagation

4.5.1. Model performance verification

This step compares traditional conditional probability with conditional probability combined with a noisy-or model. The aim is to demonstrate that a noisy-or model can provide a more accurate quantification of supply chain disruption based on unknown factors and avoid being overly absolute.

4.5.2. Cross-tier disruption analysis

For supply chains, disruption transmission exists in the supply relationship between upstream and downstream, as shown in Fig. 3. In the analysis process, the differences between non-cross-tier and cross-tier supply chain structures are compared.

4.5.3. Ripple effect analysis

This step considers the disturbance to the shipbuilding supply chain caused by the ripple effect. Forward propagation begins with the current disruption. It predicts how it will evolve into a larger issue in the future. Shipyards can identify the most vulnerable links in the supply chain and those most susceptible to interference. Backward propagation helps identify both direct and indirect causes of disruptions.

4.5.4. Sensitivity analysis

Sensitivity analysis is used to evaluate the impact of each node on the probability of shipyard disruption, enabling decision-makers to assess the system’s responsiveness to individual parameter modifications and identify the most critical aspects.

5. Numerical experiment based on the J Shipyard

J Shipyard, founded in 1865 and located in Shanghai, is one of China's oldest shipbuilding enterprises. As one of China's earliest modern shipyards, it has evolved into a key player in China's shipbuilding industry. Choosing J Shipyard's position in China's shipyards is extremely important, and its five-tier supply chain structure aligns with industry typicality.

5.1. Composition of supply chain

This study categorizes J Shipyard's supply chain into five levels using relevant research and industry reports. Ship design, component manufacturing, assembly, and market-focused activities are conducted at the shipyard. Subsystem providers for control, detection, navigation, communication, countermeasure, and piping systems are categorized at the secondary level. Primary or subsystem suppliers provide shipyards with onboard systems, components, and services. The third level includes equipment suppliers who supply components directly to second-level subsystem suppliers and, in some cases, the first-level shipyard. These suppliers provide core and leading manufacturers with critical parts and equipment. Parts suppliers supply valves, outfitting, machinery, electrical parts, deck fittings, and forged and cast parts to the first three levels. Final-level raw material suppliers supply steel, coatings, welding supplies, non-metallic materials, and energy materials to previous levels. Therefore, the shipbuilding supply chain network is illustrated in Fig. 2.

This study develops the shipbuilding supply chain network according to J Shipyard's manufacturing processes. The extensive number of supply chain nodes, along with strong business contacts and inter-level exchanges, results in a substantial quantity of connecting edges inside the shipbuilding supply chain model. The cross-tier network (Fig. 3) consists of 23 nodes and 98 edges, reflecting 60 % of the actual connection density.

5.2. Data sources for the shipbuilding supply chain

5.2.1. Factor identification and quantification

This section examines the factors contributing to supply chain disruptions. We use these identified factors to construct a BN and explain how to assign probability values to them. Three variables are commonly utilized to measure the sub-factors: Boolean variables, continuous variables, and ranking node methods. This study concentrates exclusively on Boolean variables. As discussed in 4.1, the classification of suppliers in the multi-tier shipbuilding supply chain is detailed. Nonetheless, owing to the confidentiality of the shipbuilding industry, there is limited specific information on the factors influencing suppliers' operations. Therefore, this study begins by examining the causes of difficulties in the supply chain and thoroughly evaluates the related literature on "supply chain disruptions" and "supply chain risks" from the Web of Science database. Based on citation frequencies, five essential factors were determined: human, environmental, economic, technological, and performance factors, as shown in Table 2.

5.2.2. Data generation

In conducting disruption probability analysis, Bayesian networks

Table 2
Description and Source of Supply Chain Disruption Risk Factors.

Risk Factor	Variable Name	Modeling Technique	Modeling Description	Reference
Human Factors	Stress	Boolean	It is assumed that there is a 10 % chance of making mistakes under a certain level of pressure, while there is a 90 % probability that there will be no mistakes.	Hossain et al., 2024
	Lack of Experience	Boolean	The chance of inexperience is 10 % and the probability of not occurring is 90 %.	
	The Complexity of Operation	Boolean	The complexity of operation indicates that there is a 10 % probability that the complexity of operation might lead to a greater likelihood of human error, and 90 % of the time, it would not.	
	Sabotage	Boolean	The probability of sabotage disruption under human factors is 10 %, and 90 % of the time, it would not happen.	
Environment Factors	Natural Disaster	Boolean	It is assumed that there is a 10 % probability that natural disasters will lead to supply disruptions and a 90 % probability that they will not.	Sakib et al., 2021; Meng et al., 2023; Hossain et al., 2024
	Man-Made Disaster	Boolean	It is assumed that there is a 20 % probability that man-made disasters will lead to supply disruptions and an 80 % probability that they will not.	
	Other Environmental Disaster	Boolean	The other environmental disasters node is considered to specify where 20 % of the time environmental disasters may disrupt, where 80 % of the time.	
Economic Factors	Repair Cost	Boolean	There is a 30 % possibility that the supplier will not conduct maintenance, resulting in a disruption, while there is a 70 % probability that it will not.	Sakib et al., 2021; Hossain et al., 2022
	Unit Cost	Boolean	It is assumed that there is a 10 % probability that the unit cost will exceed the profit level, resulting in a supply disruption, and a 90 % probability that it will not.	
Risk Factor	Variable Name	Modeling Technique	Modeling Description	Reference
Economic Factors	Operating Cost	Boolean	The operating cost may lead to supply delays and mistakes in 10% of cases, while it will not in 90% of cases.	
Technical Factors	Reliability	Boolean	It is assumed that there is a 10% chance that reliability will go wrong, while there is a 90% probability that it will not.	Sakib et al., 2021′; Hossain et al., 2022; Hossain et al., 2024
	Delivery Flexibility	Boolean	Approximately 90 % of the time, delivery flexibility will positively contribute to responsiveness, while 90 % of the time, it will not.	
	Malfunction of Technical Component	Boolean	It is assumed that there is a 90 % likelihood that the malfunction of tech components will create technical issues.	
	Data Quality	Boolean	Data quality being 90 % True indicates a 90 % chance that the data transfer quality would remain as expected, while a 10 % chance that the quality would drop or not be as expected.	
	Responsiveness	Boolean	It is assumed that there is a 30% chance of a disruption occurring in the response level, while there is a 70% probability that it may not happen.	
Performance Factors	Supplier Quality	Boolean	The supplier's quality has a 10% chance of causing risks and a 90% chance of not.	Sakib et al., 2021; Meng et al., 2023; Hossain et al., 2024
	Serviceability	Boolean	There is a 20% possibility that operational complexity will lead to human errors, while in 80% of cases, it will not.	

rely on historical data or expert assessments to derive prior probabilities. Nonetheless, both approaches possess constraints. Actual data frequently encompasses sensitive industry knowledge or trade secrets; numerous firms have neither established nor disclosed risk data about their production processes. This difficulty is especially common in sectors such as shipbuilding, where operational data is frequently deemed proprietary and confidential. Expert judgment can promote subjectivity and amplify uncertainty. To mitigate these constraints, e.g., Hosseini et al. (2019) posited that the probability is evaluated at a specific value; Liu et al. (2021a) employed a fuzzy probability interval for disruption analysis; Hossain et al. (2020) directly asserted that the probability of an influence subject to a Boolean distribution is a fixed value. This study employs assumptions derived from current literature and produces probabilities using Beta distributions ($\alpha = 1$, $\beta = 1$), as they are suitable for the [0,1] interval and can simulate uniform uncertainty. Many researchers have utilized this approach for probability computations (Feng et al., 2021; Nicknezhad et al., 2024).

Utilizing literature-derived assumptions, we can produce credible disruption probability figures that accurately represent real-world risk scenarios while ensuring anonymity and reducing dependence on subjective expert assessments. It addresses the issue of data unavailability in highly confidential businesses, exemplified by the J shipyard instance, and offers a reusable theoretical framework for future research. It is important to note that assumptions have already been made regarding the beta distribution in section 3.1.

5.2.2.1. Acquisition of disruption probability. As known from section 4.2.2, we have determined the probabilities and influence relationships of the secondary factors that cause disruptions at each level. At the same time, we use the Bayesian theorem formula to find the probabilities of these influencing factors. The results are shown in Table 3.

5.2.2.2. Acquisition of prior probability. Take this data as the threshold for the disruption rate and combine it with the beta distribution to generate the node data for each level. This approach helps prevent data insufficiency and reduces reliance on subjective expert opinions. As mentioned earlier, select 60 % of the edges as references. The results are shown in Table 4 below.

Table 3
Disruption Probability at the Supply Chain Level.

Supply Chain Level	Influencing Factors	Probability of Disruption
Raw Material Suppliers	Natural Disasters; Man-made Disasters Other Environmental Disasters; Unit Cost	0.48
Component Suppliers	Natural Disasters; Unit Cost; Reliability Responsiveness; Supplier Quality	0.54
Equipment Suppliers	Natural Disasters; Unit Cost; Reliability Data Quality; Responsiveness; Supplier Quality	0.59
Block Manufacturing Plants	Lack of Experience; Operational Complexity Sabotage; Reliability Malfunction of Technical Component Data quality; Responsiveness; Supplier Quality	0.63
Shipyards	Stress; Repair Cost; Operating Cost Reliability; Delivery Flexibility; Data Quality Supplier Quality; Serviceability	0.67

Table 4
Disrupt the Prior Probability of Node Suppliers at Each Level.

Node	Disruption Probability	Node	Disruption Probability
E	0.02	B1	0.07
D1	0.04	B2	0.09
D2	0.03	B3	0.06
D3	0.03	B4	0.07
D4	0.03	B5	0.07
D5	0.03	B6	0.06
D6	0.04	A1	0.14
C1	0.06	A2	0.11
C2	0.06	A3	0.13
C3	0.05	A4	0.13
C4	0.05	A5	0.13
C5	0.04		

5.3. Result analysis

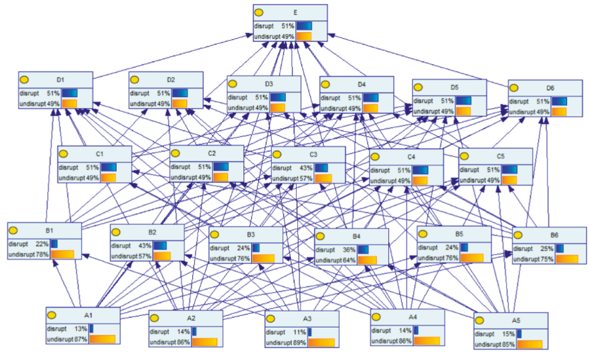
5.3.1. Model performance verification

The integration of the BN with a leaky noisy-or model demonstrates superior performance compared to the traditional BN and is more comprehensive in analysis. For example, valves (B1) and two root nodes, coatings (A2) and welding (A3), can be used to construct a local network. Since there is no influence between the two root nodes, the local network can satisfy the noisy-or gate model. The conditional probability is generated according to Bayesian estimation. Suppose we define the leakage factor xi as obeying a Gaussian probability density with a 99 % confidence level.

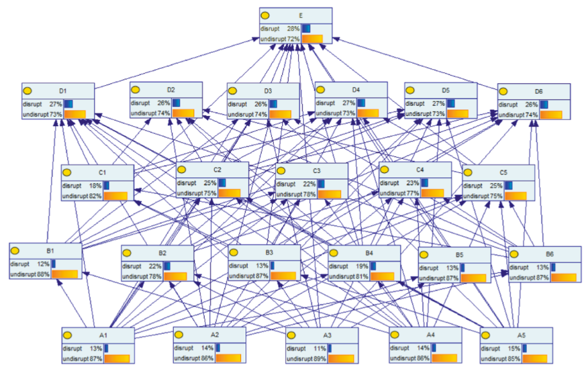
The three subplots in the Fig. 6 represent the traditional BN versus cross-tier BN with a leaky noisy-or model. When the starting probabilities of the bottom events are uniformly distributed, the probability of the top event occurring in the traditional BN (Fig. 6(a)) is 0.51, while the probability in the BN based on the proposed model (Fig. 6(b)) is 0.28. Numerical simulations verify the superiority of BN in quantifying cross-tier supply chain risks. In a situation where raw material supplier A1 is directly linked to assembly plant C1, the suggested BN reduces the chance of shipyard disruptions from 0.51 to 0.28, representing a 45.1 % decrease, and outperforms older models in complex supply chains. This improvement stems from the model's ability to represent separate trigger events for different paths,such as A1 to C1 to E and A1 to B1 to D1 to E, which better matches the complex nature of real supply chains. Simultaneously, the leakage factor (leakage probability = 0.01) measures the risks between different levels that aren't directly connected. For example, how geopolitical conflicts affect A1 and C1 together. This further shows the effectiveness of the BN model in analyzing disruptions that spread through connected supply chains, giving solid support for studying complex supply chain disruptions.

To further verify the validity of the BN combined with a leaky noisy-or model, the influence of unobserved risk on outage propagation is quantified by adjusting leakage probability parameters. Take node B1 (valve supplier) as an example, which plays a key component supplier role in the supply chain and has cross-tier connections with upstream raw material suppliers (A1) and downstream shipyard (E). Compared with the leakage phase ratio of 0.01, the outage probability of node E increases to 29 % when the leakage probability is 0.05 (Fig. 6(c)), a 3.6 % rise, indicating that the unobserved risk has a significant but limited marginal impact on the overall network through node B1.

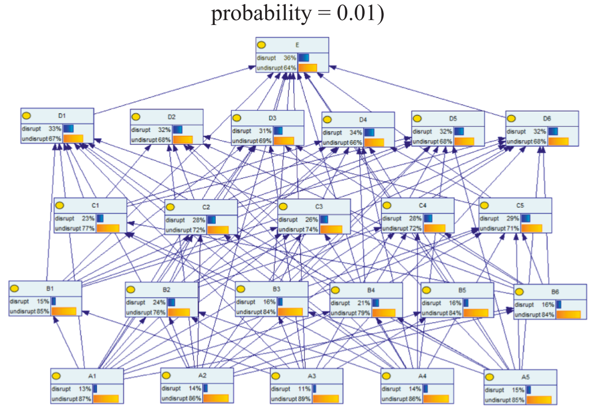
In this study, the superiority of the BN in quantifying cross-tier supply chain risks is verified through numerical simulations. Compared to the traditional BN, the new model that uses the noisy-or gate and leakage factors, greatly enhances the ability to analyze how disruptions spread across different levels of the supply chain. For example, in J-based shipyard structures, where raw material supplier A1 is directly linked to assembly plant C1, the new model reduces the chance of disruption at the shipyard (node E) from 0.51 in the traditional BN to 0.28, representing a 45.1 % decrease. This improvement comes from the model's ability to represent separate ways that disruptions can



(a) A Bayesian Network of the Cross-tier Shipbuilding Supply Chain



(b) Bayesian Network of the Cross-tier Shipbuilding Supply Chain with Leaky Noisy-OR (leakage probability = 0.01)



(c) Bayesian Network of the Cross-tier Shipbuilding Supply Chain with Leaky Noisy-OR (leakage probability = 0.05)

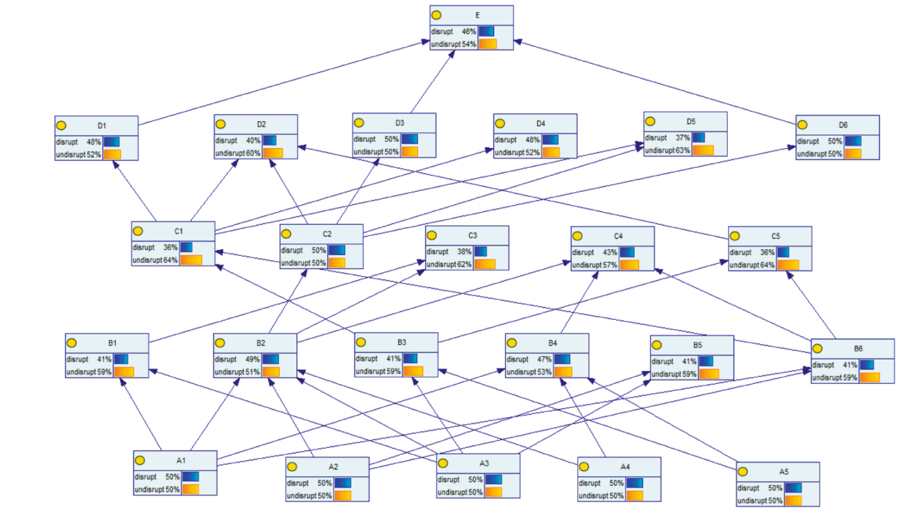
Fig. 6. Effect of Bayesian Network in Analyzing Cross-tier Shipbuilding Supply Chain.

spread through different paths, such as A1 to C1 to E versus A1 to B1 to D1 to E, which better matches the complex nature of real supply chains. By quantifying cross-tier risks that are not directly related (e.g., the joint impact of geopolitical conflicts on A1 and C1). By changing the leakage probability settings for the cross-tier hub node B1 (valve supplier), the leakage probability model not only proves its ability to identify hidden risks but also shows how unobserved risks propagate through different paths in a complex manner. This indicates that the cross-tier network structure (e.g., D1 can obtain an alternative supply of B2 through a cross-tier connection) significantly inhibits risk diffusion, which makes the marginal change in the global outage probability show attenuation characteristics. It provides a quantitative basis for the resilience optimization of highly customized industries.

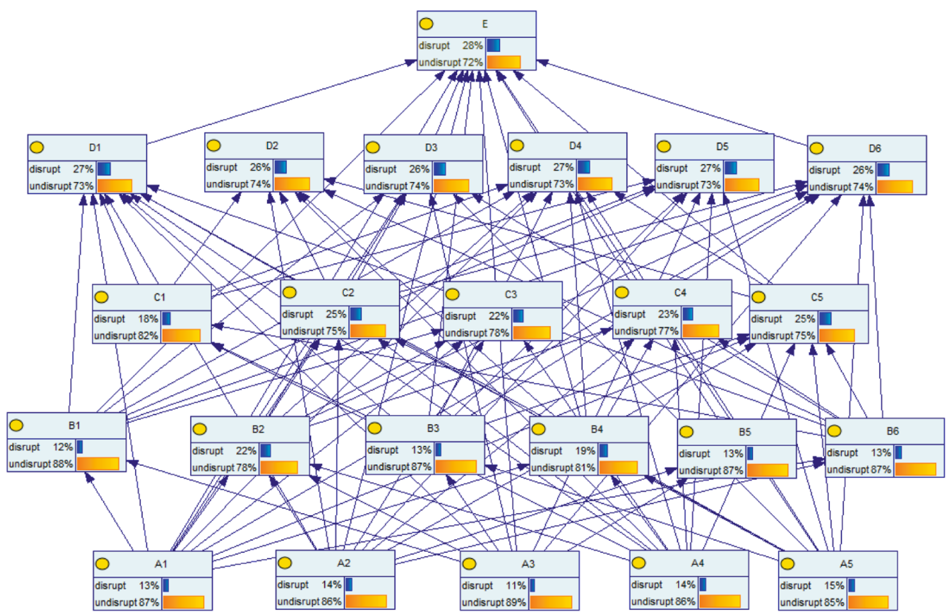
5.3.2. Disruption analysis of cross-tier shipbuilding supply chain

This part shows how well supply chain networks can handle problems by comparing two different setups: non-cross-tier and cross-tier, as illustrated in Fig. 7. To simulate realistic disruption propagation dynamics, 60 % of connection edges were selectively retained based on the network simplification criteria detailed in section 4.1. Numerical analysis reveals critical insights into risk mitigation mechanisms enabled by cross-tier connectivity.

In a non-cross-tier architecture (Fig. 7(a)), the connections between nodes follow a strict linear hierarchical relationship, e.g., A to B to C to D to E. For example, an outage at node C2 directly affects downstream D2, causing the outage probability of D2 to increase from its baseline value of 27 % to 54 %. This reliance on a single path makes the impact of a single failure: when C2 fails, it prevents D2 from getting the important supplies it needs, and without another supply option, the chance of production halting increases. Under this structure, the hierarchical isolation of nodes limits the flexibility of resource allocation, allowing local outages to evolve into systemic crises quickly. The cross-tier supply chain (Fig. 7(b)) significantly improves the robustness of the network by introducing bidirectional connections (e.g., A1 to C1, B2 to D2) and



(a) Shipbuilding Supply Chain with Non-Cross-tier



(b) Cross-tier Shipbuilding Supply Chain

Fig. 7. Disruption Analysis of Cross-tier Shipbuilding Supply Chain.

cross-tier redundant paths (e.g., A5 to C5 to E). When C2 is disrupted, its effects are partially offset by multi-path propagation:

(1) Direct cross-tier alternative: Node B2 (component vendor) can provide alternative input to D2 directly through cross-tier connections, thereby bypassing the disrupt node of C2.
(2) Multi-source supplies spread risk: D2 receives inputs from both C2 and B2, allowing the other node to compensated for disruptions at either node partially.
(3) Reduced dependency strength by path redundancy: Cross-tier connections reduce the direct dependence between nodes. For example, node E not only depends on supplier D but also obtains key resources through cross-tier connections of level C.

As shown in Fig. 7, cross-tier networks cut outage probability by over 10 % via path redundancy. Their connectivity structure enables bidirectional, cross-level product supply–demand exchanges, boosting node collaboration and reducing operational risk. In supplier-shipyard supply chains, this offers a framework for proactive disruption risk identification and mitigation. For example, shipyards can assess the network to pinpoint critical nodes and risks, optimizing resource allocation and partner selection. When disruptions occur, the network simulates supply scenarios accurately, enabling multi-channel supply to mitigate individual node disruptions' impact, minimizing delays and cost hikes. This provides a reliable strategy for navigating challenges, fostering adaptive, resilient supply chain management and driving its advancement.

5.3.3. Ripple effect analysis

This section analyzes the propagation of the ripple effect by simulating disruptions at the upstream node (e.g., A1), downstream node (E), and intermediate node (e.g., C2). The systematic adjustment of occurrence probability reveals critical insights into the propagation of cross-tier disruption. The analysis results show the disruption of the ripple effect and its impact on both upstream and downstream suppliers and shipyards.

5.3.3.1. Upstream node. Through adjusting to the occurrence probability of the bottom event in the multi-tier and cross-tier supply chain and setting the bottom node A1 (supplier) as the target node, the disruption probability of the top node E (shipyard) exhibits a near-doubling from 50 % in Fig. 8(a) to 46 % as quantified in Fig. 8(b), with ripple effects permeating adjacent levels: node B1 increased from 50 % to 57 %, node C1 shifted from 32 % to 41 %, and node D1 increased from 50 % to 49 %.

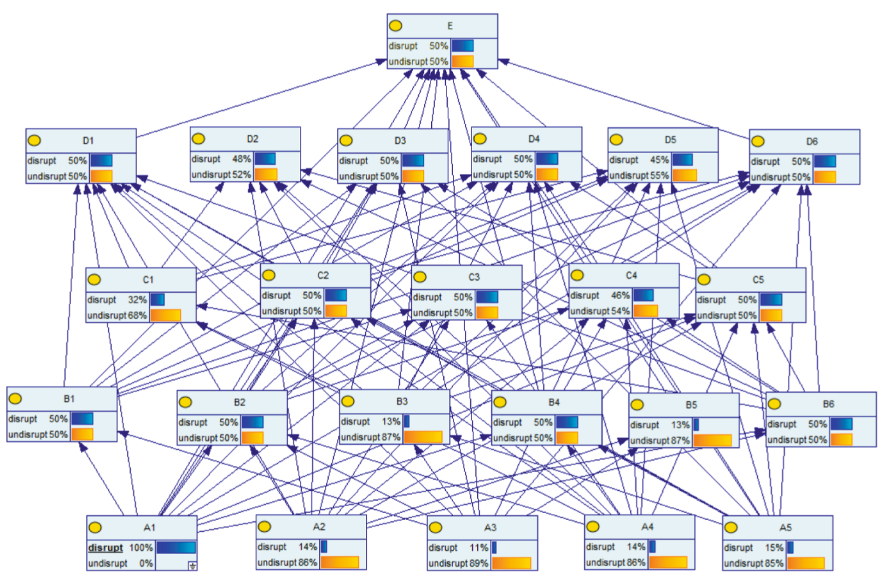
Comparative analysis reveals network topology critically regulates risk propagation. In cross-tier structures, terminal node E exhibits a 50 % disruption probability marginally higher than linear networks, while key intermediate nodes B1 and C1 show significant reductions of 12.3 % and 21.9 % respectively. This divergence stems from fundamental path restructuring: linear networks accumulate risk through sequential dependencies (e.g., D1 to E impact), whereas cross-tier designs disperse E's exposure across multiple pathways (C1, D1, B2). Intermediate nodes gain resilience through multi-path supply; B1's risk dilution occurs via redundant B1 to D2 connections, splitting impacts between B1 to D1 to E and B1 to D2 to E paths. Similarly, C1's diamond topology with direct E links reduces failure likelihood.

Notably, D1's outage probabilities converge across both topologies due to technical interface dependencies with C2, limiting B2 to D2 alternatives. This demonstrates that resilience requires synergistic structural optimization and technological adaptation. Backward Bayesian inference confirms cross-tier topologies alter conditional independence through V-type structures (e.g., A1 to C1 to B3), creating common-effect relationships that dynamically balance disruption via multi-parent probability updates. Such optimization transforms centralized risk into distributed manageable units through structural hole utilization.

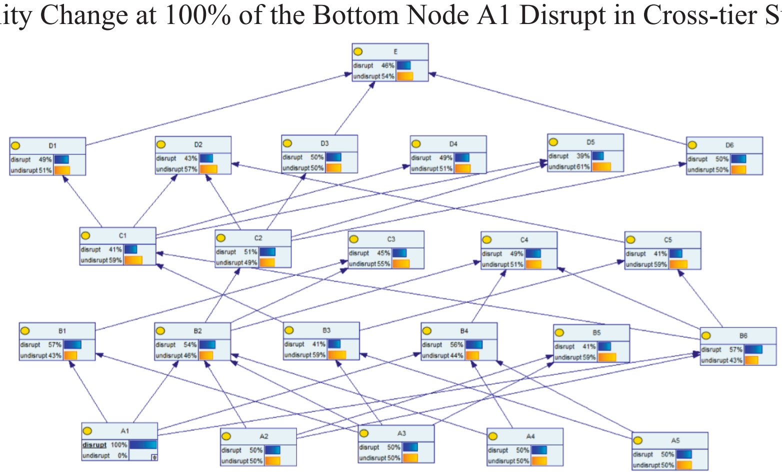
Although terminal nodes may experience slightly elevated exposure, cross-tier networks provide critical advantages: multiple risk-dispersing pathways enhance recovery agility and offer sustainable uncertainty navigation for customized industries like shipbuilding. This necessitates shifting from risk reduction to proactive risk planning in network design.

5.3.3.2. Downstream node. By adjusting the frequency of the top event and designing it as E in the multi-level and cross-tier supply chain, the main focus, with a disruption probability of 100 % is shown in Fig. 9(a).

Cross-tier connections significantly reduce disruption propagation risks. When terminal node E experiences disruption, critical node probabilities increase substantially: A1 rises from 23 % to 50 %, B1 from 22 % to 41 %, C1 from 37 % to 32 %, and D1 from 58 % to 49 %. Crucially, direct A1 to C1 connections create alternative supply routes, reducing A1's disruption risk by 54 % when B1 fails. Similarly, D1's risk drops from 58 % to 49 % through B2 to D2 backup paths and flexible

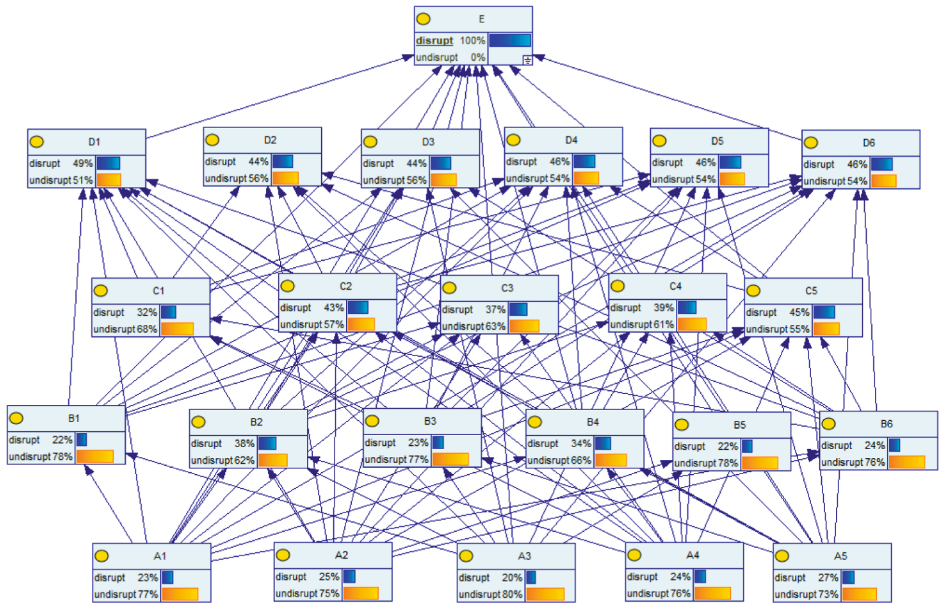


(a) Probability Change at 100% of the Bottom Node A1 Disrupt in Cross-tier Supply Chain

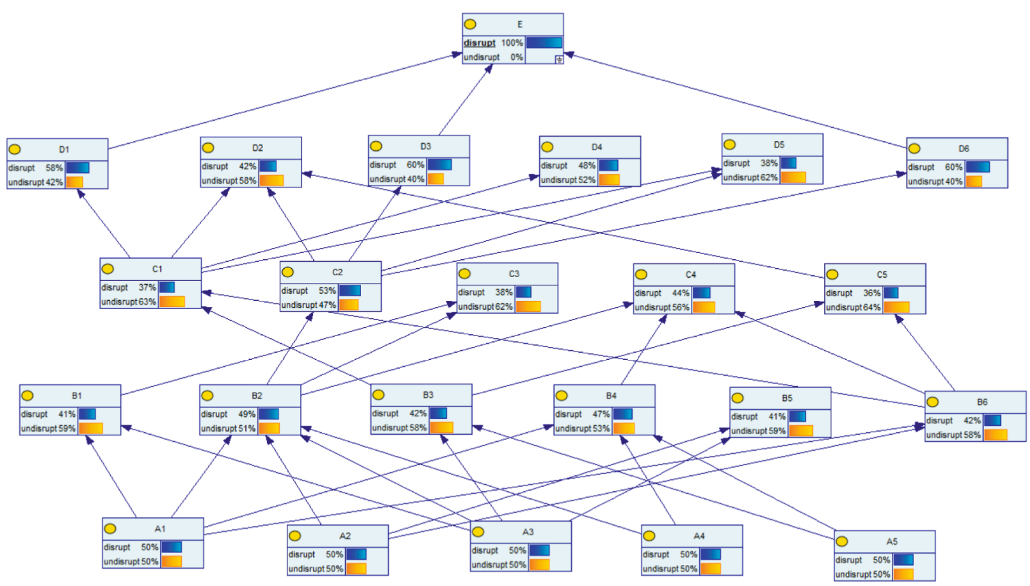


(b) Probability Change at 100% of the Bottom Node A1 Disrupt in Cross-tier Supply Chain

Fig. 8. Ripple Effect in Upstream Node.



(a) Probability Change at 100% of the Top Node E Disrupt in Cross-tier Supply Chain



(b) Probability Change at 100% of the Top Node E Disrupt in Non-Cross-tier Supply Chain

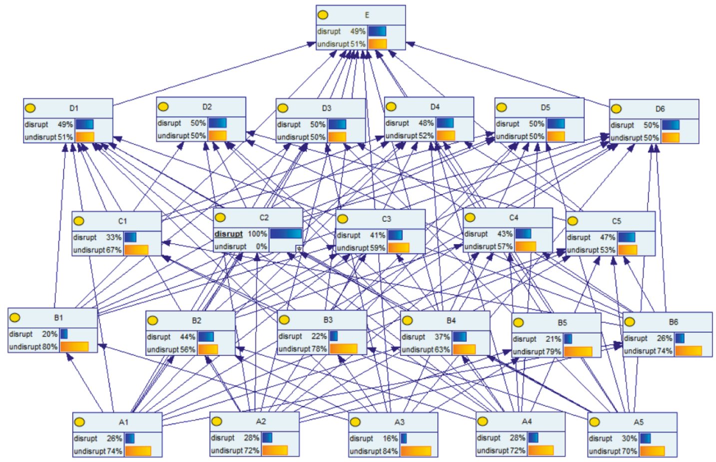
Fig. 9. Ripple Effect in Downstream Node.

feedback systems, bypassing C2 disruptions and reducing B1′s failure probability by 46 %.

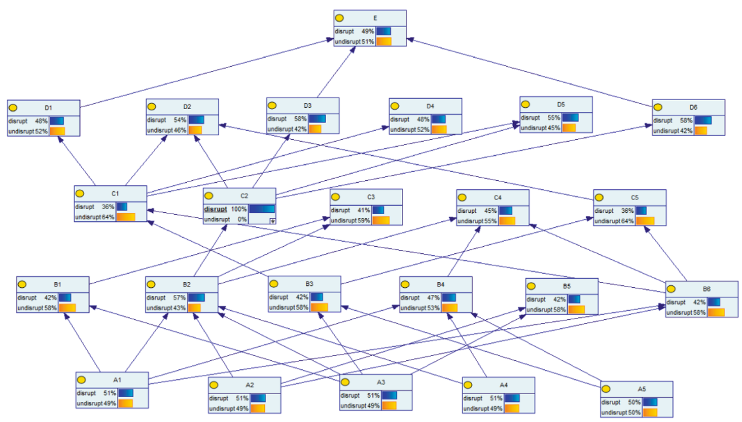
This risk mitigation operates through three mechanisms: (1) Bidirectional cross-tier relationships distribute disruption impacts; (2) Multi-source supply (e.g., simultaneous A1, B3 to C1 delivery) reduces failures by 13.5 % versus linear networks; (3) Dynamic information-sharing enables rapid response (e.g., B2 replenishment when D1 fails). These transform rigid connections into flexible networks that mitigate single-point vulnerabilities.

The structural optimization enhances robustness through inter-tier collaboration, particularly for critical nodes. Cross-tier mapping reveals risk propagation pathways while enabling closed-loop control for complex disruptions (geopolitical conflicts, shipping delays). For shipbuilding supply chains, this necessitates: (1) Establishing priority connections between strategic nodes; (2) Implementing multi-route systems to strengthen network-wide resilience. This approach shifts risk management from passive reduction to proactive planning in customized manufacturing environments.

5.3.3.3. Intermediate node. All the probabilities in Fig. 10(b), which are 51 %, 42 %, 48 %, and 49 %, all have increased. Cross-tier connections fundamentally alter risk propagation through path-switching and risk-isolation effects. By establishing backup paths between non-adjacent tiers (e.g., A1 to C1), disruptions localize upstream impacts while downstream nodes remain vulnerable due to technical dependencies. Quantitative analysis confirms: When C2 disruption blocks standard routes, A1 redirects 43 % of its load through C1, reducing failure risk from 51 % to 28 %. Similarly, B1 bypasses C2 via B1 to D2 connections, cutting outage probability by 52.4 %. This demonstrates effective prevention of upstream risk cascades. However, D1 and E exhibit comparable outage probabilities across network topologies due to



(a) Probability Change at 100% of the Intermediate Event C2 Disrupt in Cross-tier Supply Chain



(b) Probability Change at 100% of the Intermediate Event C2 Disrupt in non Cross-tier Supply Chain

Fig. 10. Ripple Effect in Intermediate Node.

technological lock-in. As a specialized subsystem manufacturer, D1′s production remains intrinsically coupled with C2′s interfaces—core components cannot be substituted via B2 to D2 cross-tier alternatives. This limitation reduces D1′s disruption probability improvement to just 2 %, highlighting how technical constraints can limit structural redundancy benefits.

These results establish cross-tier design's necessity through: (1) Upstream risk isolation via path fractals, and (2) Selective resilience enhancement despite downstream technological constraints. For customized industries like shipbuilding, this implies: Under technology lock-in realities, priority should be given to implementing cross-tier connections at upstream levels. This strategy improves whole-network fault tolerance through structural redundancy where technically feasible, while acknowledging interface dependencies at specialized downstream nodes. The approach provides critical resilience optimization pathways within real-world technical limitations.

These findings underscore the necessity for a fundamental shift in supply chain risk management, highlighting the importance of adopting a global perspective rather than merely concentrating on immediate upstream and downstream relationships. When creating strategies to respond to risks, it's important to carefully evaluate how the failure of one part can cause problems throughout the entire system and to provide warnings about risks while also preparing backup plans actively. Managers should closely monitor nodes that are significantly affected at various levels, ensuring a steady supply and mitigating the risk of disruptions by utilizing diverse supply sources and implementing other critical measures. This process involves optimizing production decisions, refining the layout of the supply network, and enhancing the supply chain's resilience to address risks arising from ripple effects effectively. These strategies are vital for ensuring the operation of the entire supply chain in the face of potential disruptions.

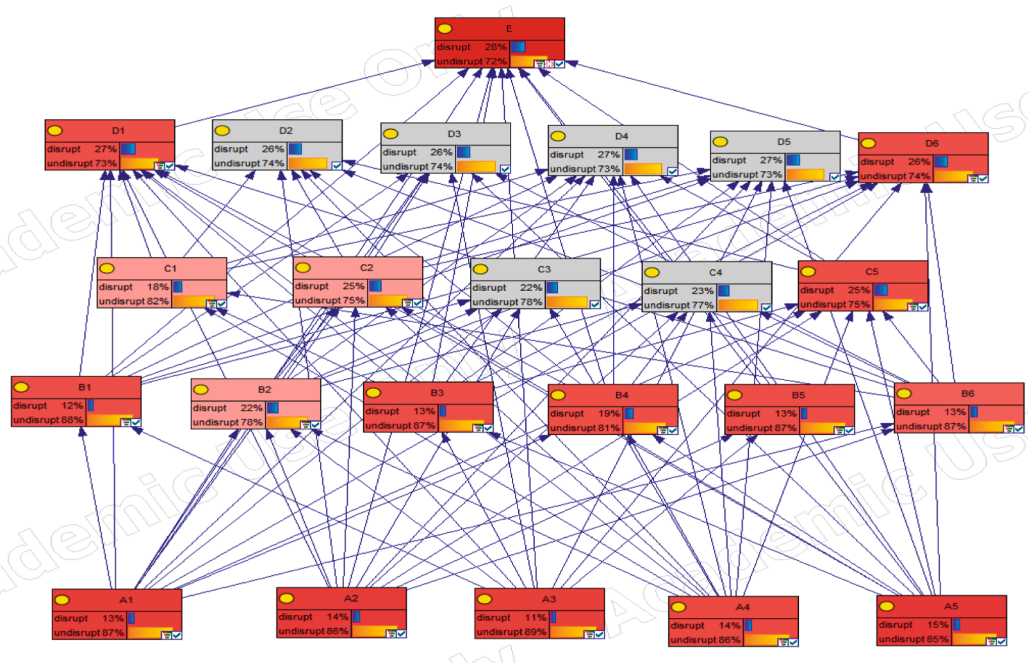
5.3.4. *Sensitivity analysis*

Based on the sensitivity analysis significance proposed in section 3.5.4, this part verifies the node risk priority. Sensitivity analysis assesses the degree to which inputs to the leaf nodes influence the root output node (Shabarchin et al.,2016; Meng et al.,2023; Chen et al.,2024). With E as the top event, Fig. 11(a) classifies nodes into three sensitivity tiers: Tier 1 includes raw material suppliers A1 (0.253), A2 (0.256), A3 (0.247), A4 (0.232), A5 (0.259), component suppliers B1, B3, B5, C5, D1, and D6; Tier 2 contains B6; Tier 3 comprises B2, C1, and C2. The tornado diagram in Fig. 11(b) confirms A5 as the most critical factor.

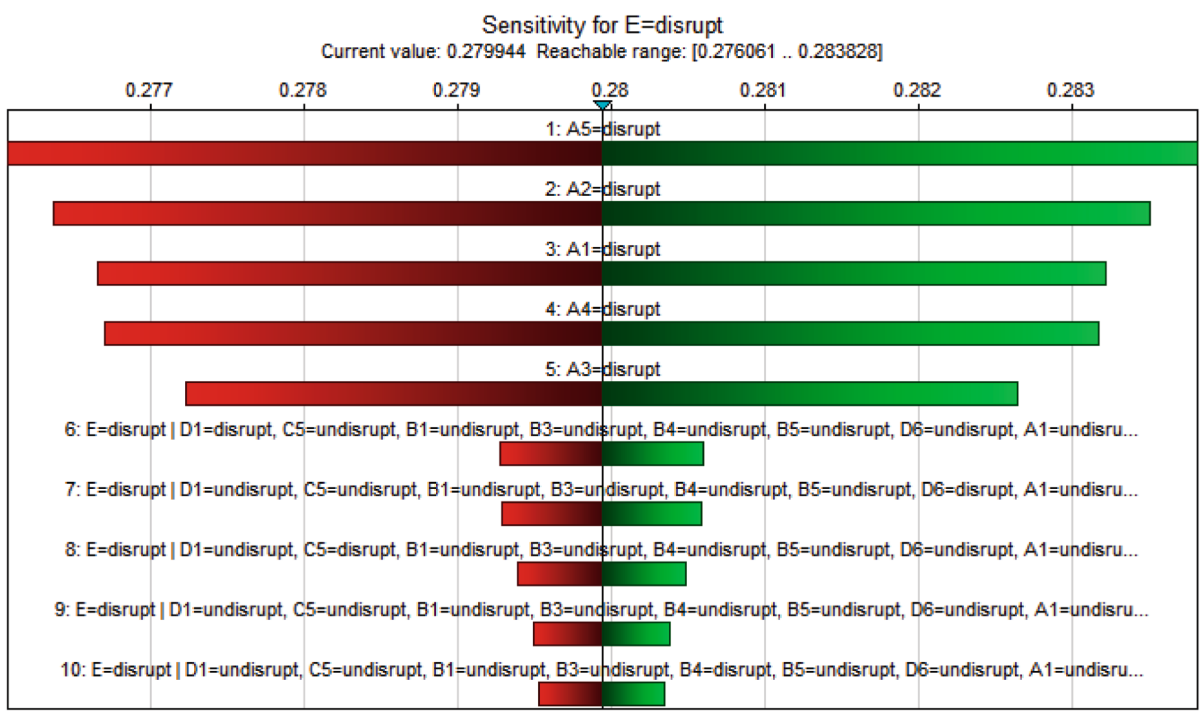
Based on these results, it can be concluded that the nodes A5, A2, A1, A4, and A3 are particularly sensitive. The main reasons for this are as follows:

(1) Fundamental position in the supply chain hierarchy

Level A suppliers are at the top of the supply chain, and the raw materials they supply are the foundation of shipbuilding. If these nodes are disrupted, the impact is progressively amplified through Levels B, C,



(a) Top-event Sensitivity Analysis



(b) A Sensitive Analysis of the Top 10 Essential Events

Fig. 11. Sensitive Analysis.

and D. The supply chain network we are also considering has cross-tier propagation, with Level A directly affecting Level C and so on, ultimately leading to production stagnation at the shipyard (Level E). This risk propagation enables small disruptions at the lowest nodes to trigger global risks.

(2) High dependence and unacceptability

In shipbuilding, certain components or equipment may be monopolized by one or a few suppliers (e.g., node A5). If there are no alternative sources, their supply disruption will lead directly to a disruption in the upstream production chain. For example, A5 with the highest sensitivity value may be responsible for supplying critical hull steel, while A2 may provide anti-corrosion coatings with high technical barriers and limited suppliers.

(3) The complexity of network connections

According to the supply chain network diagram (e.g., Fig. 3), level A nodes may simultaneously supply several level B nodes. For example, if A1 supplies raw materials to B1, B3, and B4, its disruption will affect several component suppliers simultaneously; this one-to-many link pattern expands the scope of risk propagation.

Sensitivity analysis measures the impact of risk on different points in the supply chain, enabling informed decisions about managing those risks. By leveraging these insights, managers can pinpoint high-risk nodes and implement risk mitigation strategies. For example, in shipbuilding supply chain management, both disruption of raw material suppliers and disruption of equipment suppliers might be critical factors leading to shipyard disruptions. However, by adjusting relevant variables, we can closely examine their specific impact patterns on shipyards, allowing us to pinpoint which factor indeed constitutes the core constraint. This approach optimizes the supply chain structure by averting over-reliance on single suppliers and decreasing vulnerability. Additionally, in response to evolving supply sector dynamics, managers can alliteratively conduct sensitivity analyses to dynamically monitor and adjust supply chain risk, enabling proactive and forward-thinking risk management decisions to ensure operational robustness in a complex and evolving environment.

5.4. Model extension: impact of disrupt duration on ripple effect

Based on the original model, the disruption duration threshold T_0 is introduced to construct an analysis framework under self-recovery scenarios:

Self-recovery disruption: When the disruption duration of a node is lower than the critical threshold T_0, it is defined as a self-recovery disruption, and at this time, the node passes through the internal buffer fully absorb the impact, which is equivalent to no disruption probability 100 % for the downstream of the supply chain, and the risk propagation probability is 0.

5.4.1. Result analysis

Fig. 6(b) serves as the basis for comparative analysis, as it assumes a disruption has happened and has an impact. Our research aims to bring us closer to reality and consider the impact of disruption duration on ripple effects of different nodes. The nodes A1, B1, D1, and E in Fig. 6(b) are analyzed with reference.

5.4.1.1. Upstream node. When a self-repairing short-time outage occurs in A1, the outage probabilities of B1, C2, D1 and E are 6 %, 21 %, 24 % and 25 %, respectively (Fig. 12). In the scenario of A1 with risk propagation capability shown in Fig. 6(b), the outage probability of the corresponding node increases to 12 %, 25 %, 27 % and 28 %, respectively. Comparing the two sets of data, it can be seen that when A1 realizes self-repair through an internal buffer mechanism (i.e., no risk propagation occurs), the outage probability of each node decreases.

The low outage probability of node A1 can be attributed to its built-in buffering mechanism and fault self-healing function. Within the T_0 time window, the node achieves rapid recovery through preset fault recovery procedures, effectively preventing the temporal dimension expansion and spatial dimension propagation of disruption events. As the basic node in the supply chain network, A1 assumes the pivotal function of basic material supply and service output. After the self-repair mechanism resolves the short-term disruption generated by A1, the domino effect risk transmission is not triggered. This phenomenon indicates that the single-point failure is strictly limited to the basic supply level and does not follow the cascade failure mode in traditional network propagation theory, which would spread to the middle level (such as C2) and upper nodes (such as D1, E). The empirical results are highly consistent with the theoretical assumption of fault isolation in system design and strongly verify the effectiveness of the self-healing mechanism of the

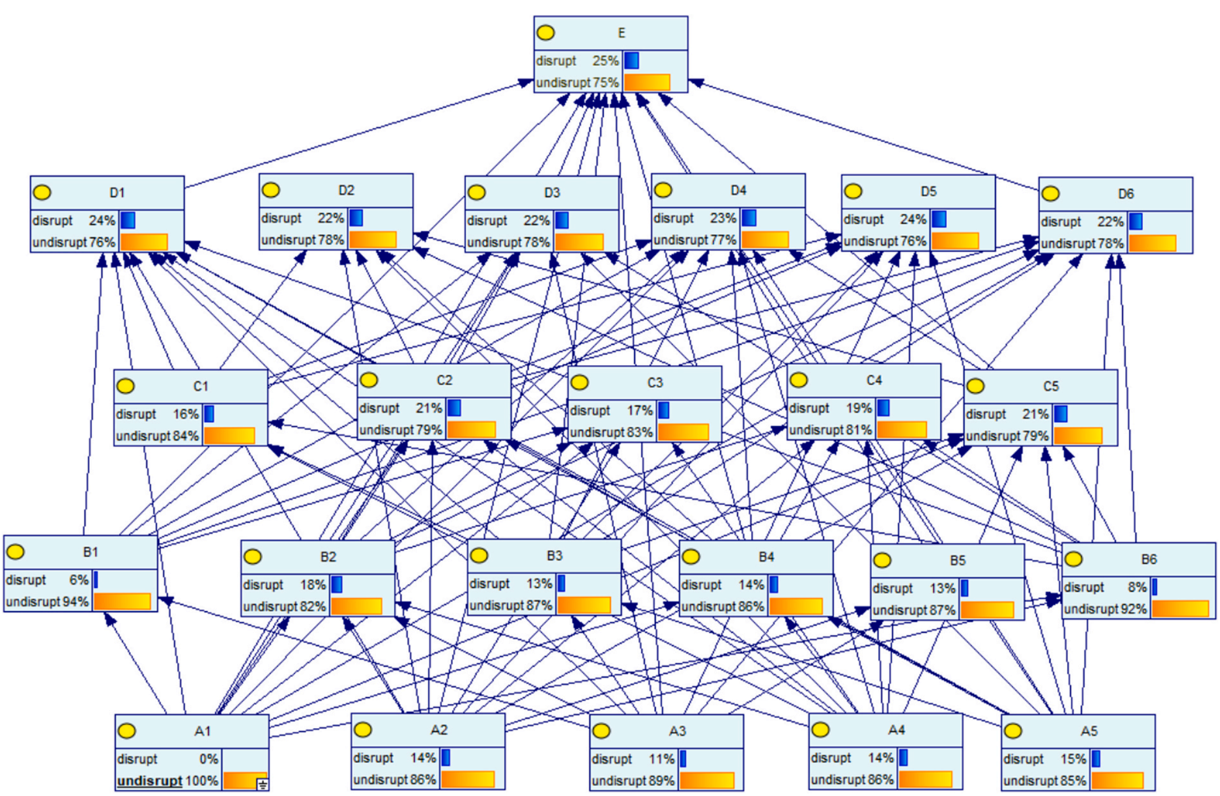


Fig. 12. Probability Change at 0% of the Bottom Node A1 Disrupt in Cross-tier Supply Chain.

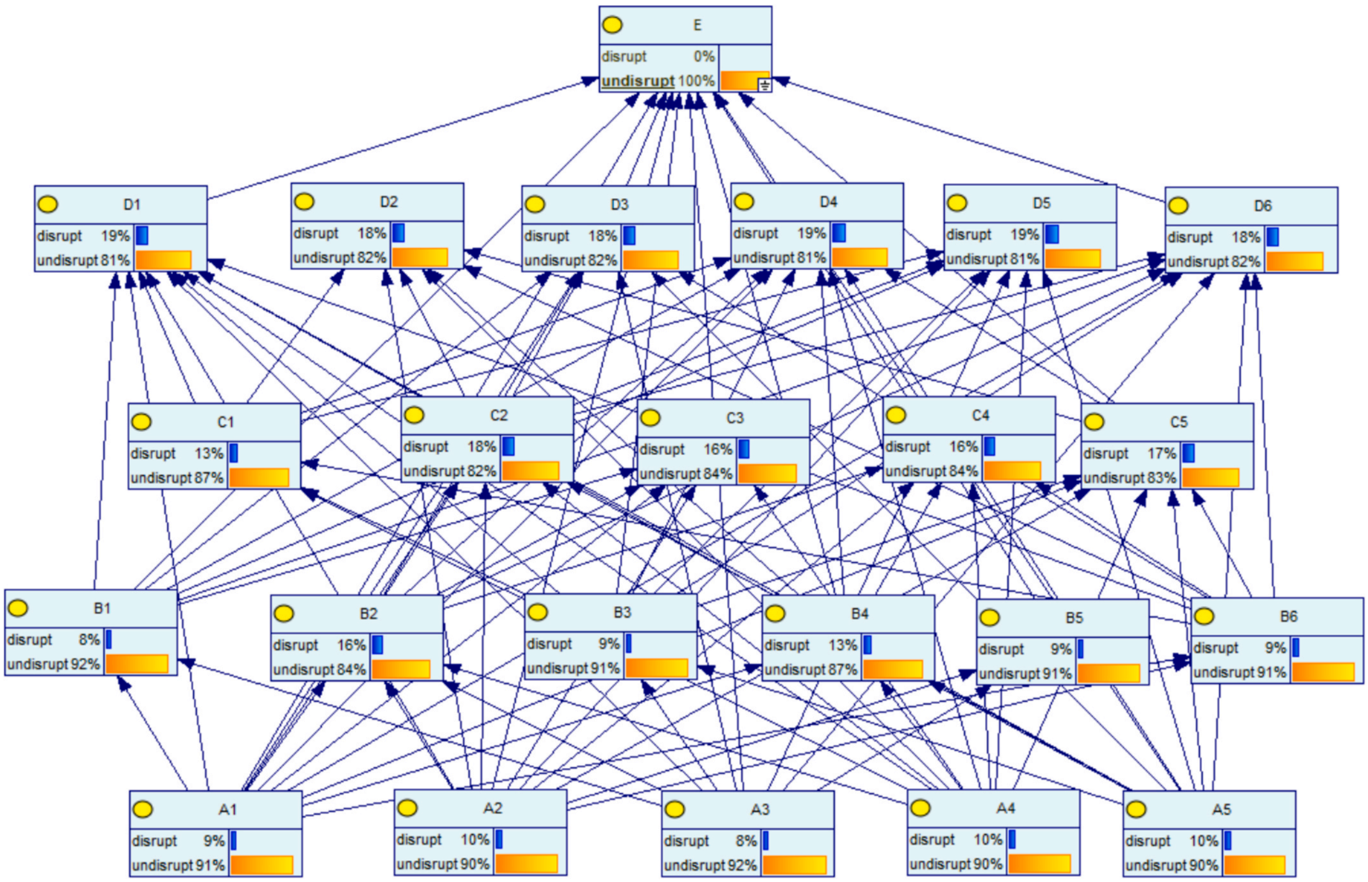


Fig. 13. Probability Change at 0% of the Bottom Node E Disrupt in Cross-tier Supply Chain.

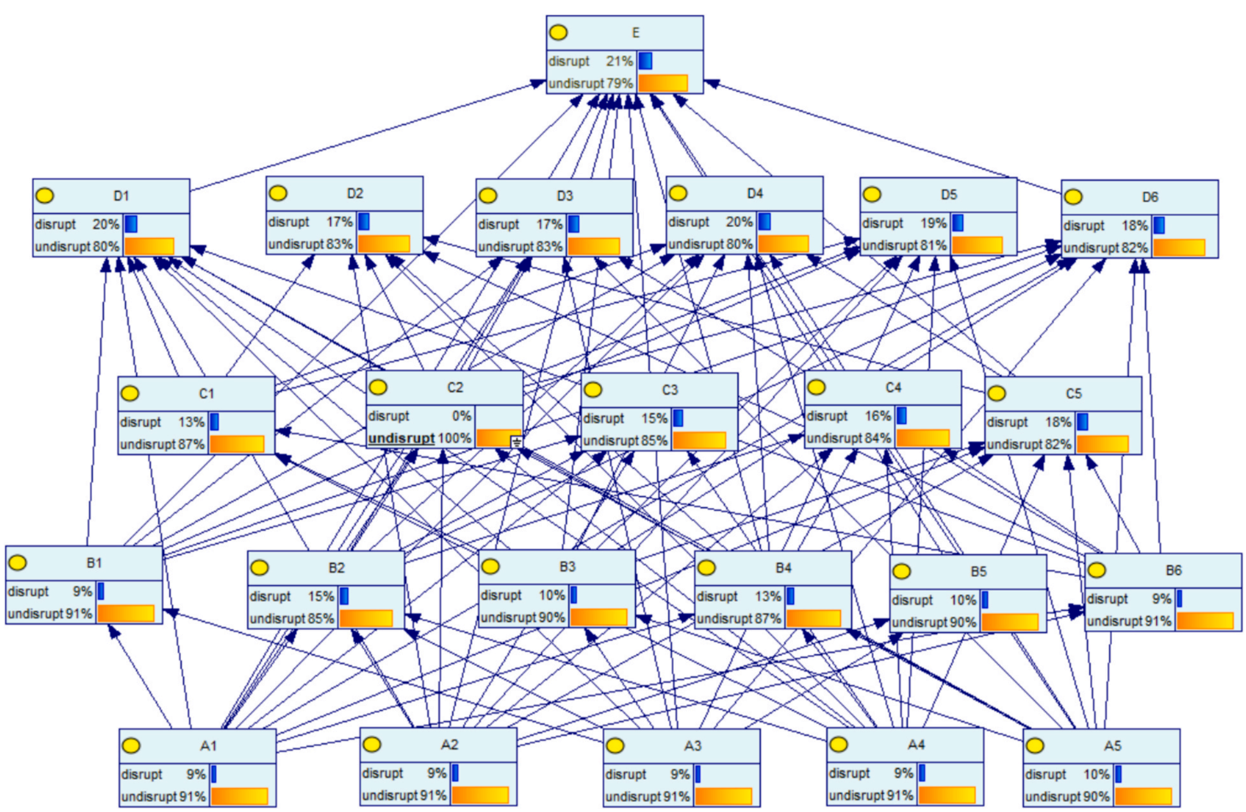


Fig. 14. Probability Change at 0% of the Bottom Node C2 Disrupt in Cross-tier Supply Chain.

bottom node in cutting off the risk propagation path and maintaining the stability of the supply chain hierarchy.

5.4.1.2. Downstream node. As shown in Fig. 13, E experiences a self-recoverable short-time disruption. The disruption probabilities of upstream and downstream nodes A1, B1, C2, and D1 are 9 %, 8 %, 18 %, and 19 % respectively. In the scenario, E has a risk propagation capability shown in Fig. 6(b). The outage probability of the above nodes increases to 13 %, 12 %, 25 %, and 27 % respectively. As the terminal execution node, E's self-repair within the critical time confines disruption impacts to the final link through two key mechanisms: (1) It prevents upstream transmission of operational feedback signals like emergency replenishment requests or order cancellations; (2) It avoids triggering cross-tier processes including quality backtracking or service compensation. Consequently, upstream nodes avoid chain reactions such as capacity rescheduling or inventory adjustments induced by terminal demand volatility.

This containment effect stabilizes production planning at D1 by eliminating sudden demand anomalies. D1 is the critical supplier directly interfacing with E. The observed risk mitigation pattern aligns with the terminal fault localization principle in system design, demonstrating how node-level self-healing: (1) Severely curtails reverse risk conduction along the supply hierarchy (from raw material suppliers A1/B1 through intermediate manufacturer C2 to top-tier supplier D1); (2) Maintains baseline resource allocation stability; (3) Reduces cross-tier disruption propagation. Empirical data confirm that E's self-repair capability not only contains local disruption impacts but significantly enhances upstream operational resilience, particularly at directly coupled nodes like D1.

5.4.1.3. Intermediate node. When C2 has a self-healing short-time outage in Fig. 14, the outage probabilities of nodes A1, B1, D1, and E are 9 %, 9 %, 20 %, and 21 %, respectively. In the scenario presented in Fig. 6(b), where C2 has a propagation risk, the outage probability of the above nodes increases to 12 %, 12 %, 26 %, and 28 %, respectively. By comparing the two sets of data, it can be found that the outage probability of each node decreases significantly when C2 does not have the risk transmission ability.

This phenomenon exhibits a distinct internal logic. First, C2 completes fault recovery through an internal buffering mechanism within the T_0 time, thereby effectively managing the duration of the disruption's impact. Second, C2 functions within the supply chain system, engaging in a bidirectional interactive role by providing services to upstream suppliers and manufacturers while simultaneously procuring goods from downstream suppliers. When the disruption fault of C2 is repaired by its buffer mechanism and does not lead to risk propagation, the single-point fault caused by it is strictly limited within the scope of this hierarchy. It is unable to spread to the upper or lower levels of the supply chain. This risk transmission characteristic is highly consistent with the design assumption of single point failure non-proliferation, and the effectiveness of the design in risk control is verified from the actual data level.

Furthermore, this self-recovery mechanism not only reduces the probability of node disruption but also enhances the overall resilience of the supply chain. This improvement enables the system to maintain stable operations in the event of accidental failures, thereby ensuring the continuity and synergy of both upstream and downstream business activities.

5.4.2. Conclusion

This study introduces a statistically derived disruption duration threshold T_0 to construct a self-recovery scenario analysis framework, revealing transmission dynamics and control mechanisms for short-term disruptions in multi-tier supply networks. Its core significance is reflected in the following two aspects:

At the theoretical level, multi-node numerical validation confirms the fault isolation stratification hypothesis: (1) Self-healing at foundational nodes severs upstream risk propagation through inventory buffering within T0; (2) Bidirectional buffering at intermediate hubs contains cross-tier diffusion via synchronized upstream or downstream capacity reserves; (3) Localized repair at terminal nodes blocks reverse demand disturbances through order flexibility protocols. This resolves cascade the limitation of theory in modeling discriminate risk spread.

At the practical level, the research results have two implications for supply chain management:

(1) Differentiated deployment of buffer mechanisms

Targeted buffer strategies should be configured according to node hierarchy characteristics. It is essential to enhance safety stock and spare capacity design at the primary supplier level to ensure a swift response to material disruptions within the T_0 time. Additionally, bidirectional buffer pools should be established at the intermediate hub node, incorporating both upstream procurement reserves and downstream delivery redundancies. Final assemblers adopt elastic order processing systems with quantity flexibility to absorb terminal volatility.

(2) Hierarchical setting of response thresholds

Establishes a multi-level risk response mechanism based on T_0. For self-recovery events with a disruption duration $t < T_0$, each level node maintains a normal operation mode to avoid resource waste caused by excessive triggering of emergency procedures. When the disruption duration $t \geq T_0$and risk propagation is activated, a cross-tier collaborative emergency plan is started to form an intelligent management and control system of threshold discrimination-hierarchical response-dynamic adjustment.

In conclusion, this study proves that the synergistic effect of disruption duration control and node self-repair mechanism is the core path to suppress ripple effects through numerical analysis and theoretical hypothesis cross-testing. This study provides a replicable methodology for risk management in ship supply chains and complex manufacturing networks. It emphasizes the importance of identifying the risk transmission characteristics of nodes at all levels. By configuring differentiated buffer strategies and threshold control mechanisms, the methodology facilitates a transformation from a passive response to disruption to active design resilience, ultimately improving the anti-interference ability and recovery efficiency of supply chain systems in uncertain environments.

6. Findings and discussion

This study systematically addresses three research questions through theoretical model, numerical experiments, and sensitivity analysis. The findings validate the effectiveness of the proposed framework in quantifying ripple effects and optimizing resilience in cross-tier shipbuilding supply chains. Below, we synthesize the results in direct response to the research question and derive actionable managerial strategies grounded in numerical experimental results.

RQ1: Bidirectional Dependency Modeling

Key findings

The bidirectional causal decomposition method successfully captures the nonlinear propagation of disruptions across tiers. Cross-tier connections reduce the probability of downstream disruption by 10.3 % compared to linear networks. For instance, when node C2 disrupts, cross-tier pathways enable partial risk isolation, lowering the disruption probability of B2 from 54 % to 49 %. This reveals the critical role of structural redundancy in mitigating ripple effects, contrasting with traditional models that assume a unidirectional risk flow.

Managerial Implications

Network Redesign: Introduce bidirectional links between non-adjacent tiers, such as raw material suppliers and assembly plants, to decouple dependencies and enhance redundancy.

Dynamic Reconfiguration Protocols: Develop predefined rules for rerouting supplies during disruptions (e.g., automated activation of B2 to D2 pathways when C2 disrupts).

RQ2: Implicit Risk Quantification

Key findings

Integrates leaky noisy-or models to quantify unobserved risks (e.g., geopolitical shocks) in cross-tier interactions, showing that a 0.04 increase in leakage probability raises shipyard disruption risk by 3.6 %. This highlights how single-level models' neglect of hierarchical hidden risks leads to underestimated systemic vulnerabilities.

Managerial implications

Hidden Risk Audits: Conduct quarterly assessments of unobserved factors (e.g., political stability, regulatory changes) for high-sensitivity nodes (A1–A5), aligning with the leakage probability framework.

Scenario-Based Stress Testing: Use the Gaussian-distributed leakage parameters identified in the study to simulate unknown-unknown disruptions and evaluate mitigation strategies.

RQ3: Structural Elasticity Optimization

Key findings

Cross-tier redundancy significantly suppresses ripple effects. Sensitivity analysis identifies raw material suppliers (A1-A5) as critical vulnerabilities, with sensitivity indices exceeding 0.23. Redundant paths (e.g., A5 to C5 to E) reduce systemic disruption risks by dispersing dependencies. For instance, A1′s direct supply to C1 lowers its disruption probability by 54 % under C2 disrupts, demonstrating the effectiveness of multi-path disruption mitigation.

Managerial implications

Redundant Pathway Activation: Predefine alternative cross-tier routes in supply chain digital twins, leveraging the 10.3 % disruption reduction demonstrated in simulations.

Supplier Diversification: Reduce reliance on single-source supplier through multi-level procurement agreements.

Integrated Strategies for Resilient Supply Chains

The following strategies synthesize findings across all RQs, ensuring alignment with empirical results:

(1) **Upstream Focus:** Prioritize redundancy in raw material and component tiers (A1-B6), where sensitivity indices are highest.
(2) **Downstream Flexibility:** Negotiate flexible order terms with shipowners to buffer delays caused by midstream disruptions (e.g., D1 disrupts).
(3) **Predictive Analysis:** Use Bayesian network outputs to forecast high-risk scenarios (e.g., port closures) and preallocate resources.
(4) **Cross-Tier Resilience Metrics:** Incorporate bidirectional risk propagation rates and leakage probabilities into supplier performance KPIs, aligning contractual penalties and rewards with the quantified ripple effects.

7. Conclusion

This paper proposes a systematic framework for analyzing ripple effects in ship supply chains across hierarchies. This study systematically compares the propagation of disruptions within ship supply chains by employing multi-level and linear models across various hierarchical structures. The findings demonstrate that hierarchical networks possess considerable resilience advantages in identifying bidirectional dependencies and concealed risks when contrasted with conventional linear models. By integrating the Bayesian network with a leaky noisy-or model, the proposed methodology advances both theoretical and practical understanding of disruption propagation in vertically integrated industries. We summarize the key contributions, managerial implications, limitations, and future research directions.

7.1. Key contributions

(1) Bidirectional causal decomposition:

Traditional models depict only one-way risk flows, but there are direct interactions across levels in the shipbuilding supply chain. In this study, we introduce cross-tier directed edges, such as A1 to C1, into the Bayesian network through bidirectional causal decomposition, thereby realizing the modeling of upstream–downstream and downstream-upstream bidirectional dependence for the first time. This method overcomes the limitations of traditional tree networks and reflects the network structure of supply chains more truly.

(2) Scene expanding:

To overcome the defect of the traditional Bayesian network in ignoring latent risk, this paper introduces a leaky noisy-or into cross-tier networks. The Gaussian distribution characterizes the probability of leakage and quantifies the combined effects of explicit risks and implicit risks. At the theoretical level, this extension enhances the Bayesian network by transforming it from a deterministic causal model into a robust analytical tool that accounts for uncertain environments. This advancement significantly improves the predictive reliability of the model in complex outage scenarios when compared to traditional Bayesian networks.

(3) Structured risk assessment:

This study provides a data-driven decision optimization framework and quantitative basis for supply chain management through sensitivity analysis and cross-tier path redundancy design. First, key node identification involves positioning high-risk levels (such as the raw material supplier level) and guiding enterprises to establish strategic inventory or diversify procurement. Second, structural elasticity optimization: Through simulation of cross-tier connections (such as A1 to C1), redundant paths can reduce the probability of downstream disruption by 10.3 %, providing a reference for designing a risk-resistant topology in supply chain networks.

7.2. Managerial implications

(1) Network Redesign for Resilience:

Introduce bidirectional connections between non-adjacent tiers (e.g., suppliers to assembly plants) to decouple dependencies and enable multi-path disruption mitigation. For example, cross-tier links (B2 to D2) reduce the impact of equipment supplier (C2) failure by 46 %.

(2) Dynamic Risk Mitigation:

Deploy data-driven tools to monitor high-sensitivity nodes (e.g., A5 for hull steel), triggering a predetermined supplier diversification strategy. Data analyzing across tiers enhances agility in rerouting supplies during disruptions.

(3) Strategic Supplier Management:

Diversify sourcing for critical raw materials (e.g., anti-corrosion coatings at A2) and maintain safety stocks to buffer upstream shocks. Sensitivity analysis highlights the importance of prioritizing redundancy in foundational tiers (A1-B6).

7.3. Limitations

(4) Data Constraints:

Probabilistic parameters rely on Beta-distributed assumptions due to limited access to proprietary industry data.

(5) Computational Complexity:

While a leaky noisy-or model mitigates parameter explosion, scaling the framework to ultra-large networks remains computationally intensive.

(6) Dynamic Decision:

This model partially solves the multi-level cross-tier disrupt analysis in a static state, ignoring that the disrupt changes with time.

7.4. Future research directions

(1) Using Real-World Data:

Future studies should validate findings with real-world operational datasets to verify the actual value of the model.

(2) Incorporating Time Variables

Extend the framework to simulate how disruptions change over time and the impact of disruptions on attracting or prolonging complex supply chains. However, the disruption effects of complex supply chain systems are time-dependent and dynamically evolving. Future research can be carried out from two core directions: time-dimensional modeling and cost-benefit integration to provide managers with real-time decisions further.

(3) Considering strategy adjustments

The model overlooks the dynamic interactions among nodes, including adjustments in supplier cooperation strategies. Subsequent studies could incorporate supplier behavior to improve the model's capacity to analyze disruption propagation dynamically.

CRediT authorship contribution statement

Yiqi Zhang: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Yanhui Ma:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition, Writing – review & editing. **Le Wang:** Conceptualization, Methodology, Visualization, Supervision, Formal analysis, Funding acquisition, Writing – review & editing. **Zhiqiong Wang:** Investigation, Supervision, Writing – review & editing. **Lixia Zhang:** Investigation, Writing – review & editing.

Declaration of competing interest

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

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Appendix A

In this study, BN combined with noisy-or model and considering leakage probability provides an effective tool for analyzing disruption propagation in cross-level shipbuilding supply chains. This appendix describes in detail the derivation process and implications of the relevant formulas.

i) Bayesian Network Basic Formula

Bayesian networks represent dependencies between variables through directed acyclic graphs, and their core is based on the Bayesian theorem:

$$P(A|B) = P(B) \bullet P(B|A) \bullet P(A)$$

Among them, $P(A|B)$ represents the probability of event A occurring under the condition that event B occurs, $P(B|A)$ is the probability of event B occurring under the condition that event A occurs, and $P(A)$ and $P(B)$ are the prior probabilities of events A and B, respectively.

In the ship supply chain disruption analysis, let X be a variable representing the state of a node in the supply chain (disrupted or normal), and Y_1, Y_2, $\cdots$, Y_n, are the parent node variables that affect X. Then the joint probability distribution of X can be expressed as:

$$\mathrm{P}(\mathrm{X}, \mathrm{Y}_1, \mathrm{Y}_2, \cdots, \mathrm{Y}_\mathrm{n}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}(\mathrm{Y}_\mathrm{i}) \bullet \mathrm{P}(\mathrm{X}|\mathrm{Y}_1, \mathrm{Y}_2, \cdots, \mathrm{Y}_\mathrm{n})$$

ii) Noisy-or Model Formula

The noisy-or model is used to assume that the parent node independently triggers the disrupt of the child node. Let child node X have n parent nodes Y_1, Y_2, $\cdots$, Y_n, and the probability that each parent node $\mathrm{Y_i}$ alone will disrupt child node X is $\mathrm{P}(\mathrm{X}|\mathrm{Y_i} = 1)$ ($\mathrm{Y_i} = 1$ indicates that the parent node $\mathrm{Y_i}$ is disrupted), and the parent nodes are independent of each other. Then, when all parent nodes are not disrupted, the probability that child node X will not be disrupted is:

$$\mathrm{P}(\mathrm{X} = 0|\mathrm{X}|\mathrm{Y}_1 = 0, \mathrm{Y}_2 = 0, \cdots, \mathrm{Y}_\mathrm{n} = 0) = 1$$

When at least one parent node is disrupted, the probability of child node X being disrupted is: $\mathrm{P}(\mathrm{X} = 1|\mathrm{Y}_1, \mathrm{Y}_2, \cdots, \mathrm{Y}_\mathrm{n}) = 1 - \prod_{\mathrm{i}:\mathrm{Y_i}=0}(1 - \mathrm{P}(\mathrm{X}|\mathrm{Y_i} = 1)$

iii) Leakage Probability Formula

To more accurately capture unobserved risk factors, the leakage probability is introduced. The leakage probability represents the probability that even if all observable parent nodes are in a normal state, the child node may still experience a disruption due to unobserved factors. Suppose $\mathrm{P_{leak}}$ is the leakage probability, then after considering the leakage probability, the probability of disruption of child node X is: $\mathrm{P}(\mathrm{X} = 1|\mathrm{Y}_1, \mathrm{Y}_2, \cdots, \mathrm{Y}_\mathrm{n}) = \mathrm{P_{leak}} + (1 - \mathrm{P_{leak}}) \bullet \left(1 - \prod_{\mathrm{i}:\mathrm{Y_i}=0}(1 - \mathrm{P}(\mathrm{X}|\mathrm{Y_i} = 1)\right)$

Appendix B

The traditional BN analysis results are shown in (a). The analysis and methods are too absolute and fail to reflect real conditions. As known from Table 4, the probability of disruption of A1 is 14 %, and the probability of disruption of A3 is 13 %. The conditional probability is generated according to Bayesian estimation. Suppose we define that the leakage factor xi obeys Gaussian probability density, and its confidence level is 99 %. The disruption probability result for B1 is shown in (b).

(a) Conditional probability Table of Traditional Bayesian Network

A1	A3	B1 = T	B1 = F
T	T	1	0
T	F	1	0
F	T	1	0
F	F	0	1

(b) Conditional Probability Table Considering Leaky Noisy-OR

A1	A3	B1 = T	B1 = F
T	T	0.519	0.481
T	F	0.5	0.5
F	T	0.5	0.5
F	F	0.01	0.99

Data availability

No data was used for the research described in the article.

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