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RESEARCH ARTICLE

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Assessing supply chain risks for chip industry with LDA and multi-layer Bayesian network method

Abstract In recent years, global geopolitical turmoil, including events like the US–China trade war and the Russia–Ukraine conflict, has significantly reshaped the panorama of the global supply chain (SC). Among these, the chip SC stands out as particularly impacted. Chips form the backbone of all electronic industries, therefore, there is an urgent need for a reassessment of SC security within the chip sector. In this study, we begin by conducting an LDA analysis on 320 relevant news reports to develop a thematic model for the Chinese chip supply chain (CCSC). This approach helps identify the key risk landscape, ultimately distilling 10 major risk factors and four mitigation strategies. Subsequently, we propose an improved multi-layer sequential Bayesian Network (BN) model to assess and quantify risks within CCSC. Lastly, we utilize sensitivity analysis and propagation analysis to examine the impact of risk factors on the ultimate risk of SC disruption and define the resilience and importance of the risk nodes. Our research offers fresh theoretical insight into utilizing BN and LDA methods for modeling SC disruption risk. Furthermore, the study reveals that talent shortage, patent infringement, and insufficient Research and Development (R&D) investment are the three most significant factors contributing to the risk of disruptions in the CCSC. These factors are not only the most critical but also the least resilient, underscoring that enhancing innovation capabilities should be the foremost priority for strengthening the CCSC. Increasing government subsidies is the most effective mitigation measure, providing greater financial support for enterprises, boosting their innovation capabilities and competitiveness, and attracting more investors to the industry.

Keywords supply chain risk, supply chain resilience, ripple effect, Bayesian network, chip supply chain

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1 Introduction

The globalization of supply chain (SC) has enabled countries to capitalize on their production and distribution strengths, leading to improved customer service and economic growth. However, recent geopolitical disruptions, such as the US–China trade war, the COVID-19 pandemic, and the Russia–Ukraine conflict, have significantly reshaped the global SC landscape (Handfield et al., 2020; Nikookar and Yanadori, 2022). With President Trump's 2018 trade war against China, tensions between the two biggest economies in the world have increased. The COVID-19 pandemic exposed the long-standing shortages of essential products, including personal protective equipment, automobiles, and semiconductor components for appliances (Ivanov and Dolgui, 2022; Magdy et al., 2024). This highlighted the vulnerabilities of the global SC. Furthermore, the supply of oil and natural gas was affected by the Russia–Ukraine conflict, leading to impacts on the availability of neon for semiconductor fabrication and fertilizers for agricultural production

(Tang, 2022). Consequently, there has been an intensified call for a reevaluation of SC security, especially in the chip SC.

Chips are the foundation of all electronic industries and have a great impact on human society. From smartphones to space stations, their widespread use is indispensable. The chip SC is currently one of the SCs most affected by geopolitical tensions (Chen et al., 2023; Zhang et al., 2025). Since Moore's Law was proposed in 1965, the development trajectory of semiconductors has been following the trend of globalization. No single country can autonomously accomplish the entire ecosystem of the semiconductor SC. However, the trade war that started in 2018 and subsequent political uncertainties have fueled anti-globalization sentiments in the chip industry. This trend has reached new heights in 2022, with the US signing the Chip and Science Act on August 9, 2022. East Asian countries and the European Union have also introduced similar laws and investment plans to support the chip industry. On October 7, 2022, the US Department of Commerce's Bureau of Industry and Security (BIS) implemented an unprecedented semiconductor export restriction policy, which included comprehensive controls on China's exports, covering products, technology, talent, terminal applications, and investments.

As China's economy continues to grow rapidly and its digitalization and intelligence levels advance, the country has emerged as the world's largest purchaser of chips. However, China's low domestic chip self-sufficiency rate has created a 'chip shortage' crisis. China ranked third in the world in 2020 with a 15% chip production capacity; however, 60% of this capacity came from foreign investment, with indigenous Chinese companies contributing just about 40% (Zhang and Zhu, 2023). The tense geopolitical situation has had a severe impact on the Chinese chip industry, creating significant SC security risks. For example, Zhongxing Telecom Equipment (ZTE) Group was sanctioned by the US in 2018 and faced bankruptcy due to its high dependence on US chip supply. Similarly, Huawei's mobile phone shipments dropped by 81.6% in 2021 after being subject to export controls. Additionally, some American chip companies, such as Intel and Micron, have withdrawn their investments from China and are exploring chip production opportunities in countries like India and Vietnam.

Amid escalating trade tensions between China and the US, coupled with multiple factors such as the impact of the epidemic and SC management, the Chinese chip supply chain (CCSC) has faced serious disruption risks. This phenomenon has spurred not only the Chinese government and businesses but also nations worldwide to reconsider the security of chip SCs critically. Despite many stakeholders foreseeing the detrimental and substantial effects that pandemics, trade disputes, and other intricate scenarios could have on their operational and SC performance (Ivanov, 2021; Fan et al., 2022a), they often lack guidance on simulating and evaluating the impact of SC disruptions.

Currently, most research on SC risk management focuses on recovery capabilities in response to "instantaneous" damages such as earthquakes and fires. However, the main distinction between the chip SC and other SCs lies in its high complexity, technical requirements, and long cycle. Chip production not only involves sophisticated processes but also relies on global supplier collaboration, making it more susceptible to external factors such as geopolitical influences (Liu et al., 2024; Longauer et al., 2024). The chip SC risks caused by geopolitical factors are not only highly random, but also exhibit long-term and repetitive characteristics, potentially impacting the stability of the SC intermittently over a long period, thereby threatening its long-term survival. The COVID-19 pandemic has raised concerns about SC resilience, which helps fill the gap in research on the long-term sustainability of SC (Hosseini and Ivanov, 2022; Ivanov, 2022). However, research on this issue remains limited. To bridge this gap, our research aims to tackle the following three key research questions:

RQ 1: What risks might political uncertainty, particularly trade frictions, pose to the stable operation of the chip SCs? This question aims to identify key vulnerabilities in the chip SC under geopolitical tensions.

RQ 2: How can Bayesian Network (BN) be utilized to quantify the risk of SC disruptions specific to the chip industry, considering risk factors and process risks in the context of trade frictions? This helps to establish a systematic approach for assessing and predicting risks specific to the chip SC.

RQ 3: How to effectively mitigate risks within the chip SC and maintain continuous oversight of SC vulnerabilities? Understanding this can provide actionable insights for enhancing SC resilience and long-term stability.

In risk identification, we use the Latent Dirichlet Allocation (LDA) method to perform topic modeling on news reports related to chip SC risks. As a topic modeling technique, LDA is particularly well-suited for exploratory analysis of unstructured data, such as media reports. It can reveal underlying risk factors by identifying key themes, without relying on predefined theoretical frameworks. In SC risk modeling, the existing approaches encompass mathematical modeling, fuzzy set methods, and multi-criteria decision-making (MCDM) methods such as TOPSIS, Analytic hierarchy process (AHP) (Nakandala et al., 2017; Schaefer et al., 2019; Mithun Ali et al., 2019; Liu et al., 2022). Nonetheless, some of these methods necessitate integration with other technologies to derive substantial conclusions, while others inadequately emphasize modeling uncertainty and risk propagation. In contrast, BN is a powerful method for handling uncertainty, risk assessment, and decision-making. It can model multiple objectives and the spread of risks from a network perspective, making it easier to model uncertainty and its impact (Pires and Barbosa, 2018). A distinguishing characteristic of BN is its unique ability to perform forward and backward propagation analysis, surpassing alternative techniques like regression modeling, structural equation modeling, or neural network modeling in capturing relationships between variables. By employing propagation analysis, the ripple effect, a chain reaction that may occur when the impact of disruption propagates and cascades downstream throughout the SC (Park et al., 2022), can be effectively modeled. Hence, our research adopts the LDA and BN methods as the principal research approach. We believe that the methodology of this study possesses a certain degree of universality and can provide valuable guidance for the identification, modeling, and assessment of other SC risks.

In our research, we crafted a multi-layer sequential Bayesian Network (BN) model, building upon the framework proposed by Hosseini and Ivanov (2022) to encompass the processes from upstream, midstream, to downstream in the industrial chain. This approach facilitates transparent modeling of risk propagation within the chip SC from a sequential viewpoint. Subsequently, the LDA method was employed to model the risks introduced by trade frictions to the CCSC, leading to the identification of 10 potential risk factors and the summarization of 4 risk mitigation measures. Finally, the proposed model is applied to model and quantify the risks within CCSC against the backdrop of the US–China trade frictions. Propagation analysis is employed to examine the impact of risk factors on SC disruption risk. Forward propagation analysis assists managers in assessing the efficacy of mitigation strategies. Conversely, backward propagation analysis enables ongoing surveillance of the SC's risk level. Most importantly, based on the characteristics of this research, we defined new quantitative indicators for the resilience and importance of risk nodes, using conditional probability to capture the ripple effects. The finding further suggests that our indicators can be valuable tools for decision-makers to identify the resilience level of the most important risk node based on forming a quadrant diagram in terms of importance and resilience.

The contributions of this study are as follows:

• Developed a multi-layer sequential BN model to simulate and assess risk propagation within the SC, encompassing upstream, midstream, and downstream processes.

• Applied the LDA method to identify 10 key risk factors and 4 mitigation measures associated with trade frictions in the CCSC.

• Proposed a novel set of quantitative indicators for assessing resilience and importance of risk nodes, using conditional probability to capture ripple effects.

• Used BN-based forward and backward propagation analyses to evaluate the efficacy of risk mitigation strategies and support ongoing monitoring of SC vulnerabilities.

The remaining sections of this paper are organized as follows: Section 2 provides a review of pertinent literature on SC disruption risk management and the impact of trade frictions on the SC. Section 3 discusses the LDA method and BN method. In Section 4, we introduce the proposed multi-layer sequential BN modeling method. Section 5 applies the LDA method for topic modeling and risk identification. Sections 6 and 7 present the simulation results and management insights derived from the study, respectively. Finally, in Section 8, we summarize the findings and provide an outlook for future research.

2 Literature review

Our study is centered around two primary research areas: SC disruption risk management and the influence of political uncertainty on SC management. First, we conducted an extensive literature review on SC disruption risk management, paying special attention to the implementation of the BN method. Then we examined the relevant literature on the impact of trade frictions on the SC. Through our analysis, we were able to preliminarily determine the major risk situations faced by the global SC, as well as the potential application of the BN method in risk management.

2.1 Supply chain disruption risk management

The methods for assessing SC risk can be broadly categorized into quantitative, qualitative, and hybrid approaches. Qualitative methods, such as Failure Mode and Effects Analysis (FMEA) and the cognitive graph method, are commonly used to identify and assess risks (Faghih-Roohi et al., 2020; Ghadir et al., 2022; Li et al., 2025; Marcucci et al., 2024). However, these methods tend to be subjective and may struggle with complex and large-scale SC environments. On the other hand, quantitative methods, including Monte Carlo simulation, fuzzy comprehensive evaluation, and other mathematical techniques, dominate the field due to their ability to provide data-driven insights (Majumdar et al., 2021; Bourgeois et al., 2023; Corsini et al., 2024; Soltanisehat et al., 2023). Despite their advantages, these methods often rely on the availability of large amounts of accurate data and may require significant computational resources, which can pose challenges in real-world applications. Additionally, hybrid methods, which combine multiple techniques to enhance the robustness of risk assessments, have gained increasing attention (Mital et al., 2018; Mithun Ali et al., 2019; Abdel-Basset and Mohamed, 2020). These methods aim to overcome the limitations of individual approaches by incorporating the strengths of different models.

Nakandala et al. (2017) combined hierarchical holographic modeling with fuzzy logic methods to create a hybrid risk assessment model that incorporates risk identification and assessment processes for determining the overall risk level. Schaefer et al. (2019) introduced a hierarchical framework that utilizes the Monte Carlo Analytic Hierarchy Process (MCAHP) to evaluate supplier risks based on their location. Mital et al. (2018) employed cognitive graph and AHP method to identify and assess SC risks across various product categories. Chen and Wu (2013) proposed an improved FMEA approach from the perspective of SC risk for selecting new suppliers and employed AHP to determine the weight of each criterion and sub-criterion in supplier selection. To address inherent uncertainties, it is common practice to combine FMEA analysis with other techniques such as fuzzy sets or gray theory. Mithun Ali et al. (2019) presented a gray-based mixed Decision-making Trial and Evaluation Laboratory (DEMATEL) model to evaluate the relationship between the main risks identified in the food SC. The methodology introduced by Abdel-Basset and Mohamed (2020) integrated the plithogenic multi-criteria decision-making approach, specifically utilizing the Technique in Order of Preference by Similarity to Ideal Solution (TOPSIS) and Criteria Importance Through Inter-criteria Correlation (CRITIC) methods. Liu et al. (2023b) emphasize how technologies such as big data, blockchain, and IoT improve supply chain resilience (SCR) by providing flexibility, visibility, and agility at various stages of risk management, although they acknowledge potential initial disruptions that can be mitigated through further technological iteration. Xue and Li (2023) focus on balancing SCR and SCE in the context of Industry 4.0, proposing a research agenda that investigates the trade-offs between resilience and efficiency. Their study highlights the need for more exploration into how digital technologies can simultaneously enhance both dimensions. Liu et al. (2023a) examine the impact of COVID-19 on sustainable supply chain resilience (SSCR), proposing mathematical models to optimize resilience measures under budget constraints, and emphasizing the prioritization of adaptive capacity measures when budgets are limited. While these studies provide valuable perspectives and methods for SC risk assessment, they each have certain limitations. For instance, many of these methods fail to adequately address the dynamic nature of SCs, particularly in rapidly changing global environments where external factors such as political, technological, or market changes can have significant impacts on SC risks. Additionally, several models rely on qualitative analysis or subjective judgment, which can introduce biases and uncertainty, limiting the robustness of the assessments.

The utilization of BN to calculate SC risk exposure and predict disruptions represents a burgeoning area of research. Librantz et al. (2021) used a combination of BN, AHP, and Noisy-OR methods to evaluate the primary risks in the software SC, and applied them to the risk level assessment and ranking of software suppliers. Hosseini et al. (2020) constructed a novel model based on discrete-time Markov chains (DTMC) and dynamic BN to quantify ripple effects and the cascading impact of supplier interruptions on manufacturers, considering total expected utility and service levels. While these research emphasizes the use of BN to evaluate SC risks, these models remain highly specialized to particular contexts (e.g., software SC or ripple effects of supplier interruptions) and are often difficult to generalize across different industries or SC types. Furthermore, the reliance on additional methods such as AHP and Markov Chains, while useful, introduces complexity that might limit the real-time applicability and scalability of these models in fast-moving environments.

Additionally, to find appropriate intervention measures, Liu et al. (2022) integrated mathematical programming methods, the do-calculus, and causal BN to create two mixed integer nonlinear programming models for disruption propagation management in multi-level SC with a limited intervention budget. However, the complexity of this approach and its high demand for computational resources may limit its real-time applicability and scalability in rapidly changing environments. Additionally, this study focuses more on interventions under budget constraints, lacking a comprehensive evaluation of long-term and recurring risks. Hosseini and Ivanov (2022) proposed a method for modeling and quantifying the impact of SC disruption following the pandemic and developed a multi-layer BN model to capture the triggers and risk events of the COVID-19 pandemic and their effects on SC financial performance and business continuity. However, this model mainly focuses on the causal relationships of risk events, making it difficult to provide a comprehensive analysis and evaluation when the supply chain faces systemic shocks. Specifically, long-term risks, such as geopolitical issues and market fluctuations, are not adequately considered. Shi and Mena (2023) introduced an event-based Bayesian approach to model causal relationships between variables at different time intervals, with the aim of assessing resilience based on operational and financial performance standards. Even so, their focus is still limited to assessing resilience under current operations and lacks an analysis of long-term risk changes, especially the potential risk propagation across industries in the SC. In summary, although these three studies contribute to SC risk mitigation, they share the following limitations: First, most focus on short-term disruptions and specific events, such as pandemics or supplier interruptions, and fail to provide comprehensive and dynamic modeling of long-term and recurring risks (such as geopolitical). Second, existing applications of BN are often limited to specific scenarios, not fully considering the risk transmission and fluctuations in the complex relationships between SC upstream and downstream. Furthermore, while complex mathematical programming and optimization methods are effective, their applicability and real-time use may be restricted in rapidly changing environments.

To address the above limitations, this study introduces the LDA method, combined with dynamic factors like trade friction, to provide a more detailed identification of SC risks. Additionally, we propose an innovative multi-layer sequential BN model to more flexibly and comprehensively address long-term and recurring risks in complex SC. The multi-layer structure of the BN captures risk propagation across the SC, overcoming the limitation of focusing only on a single risk source. This makes the model suitable not only for short-term disruptions but also for simulating the effects of long-term, recurring risks such as geopolitical tensions and market fluctuations. Finally, the proposed framework models SC risk propagation from an industry chain perspective, focusing on real-world SC management scenarios, which helps better address dynamic changes and long-term risks in complex SC environments.

2.2 The impact of political uncertainty on supply chain management

The capability of SC globalization allows countries to capitalize on their production and distribution strengths to bolster their economies while simultaneously enhancing customer service. Political factors have been instrumental in driving the globalization of SCs. However, a series of recent geopolitical tensions, such as the 2016 Brexit vote in the UK, the US–China trade war that commenced in 2018, and the Russia–Ukraine conflict in 2022, have revealed the limitations of globalization (Fan et al., 2022a). These developments signal that political uncertainty will continue to impact SC operations and management, as well as reshape the research agenda in this field.

In terms of financial responses, Fan et al. (2022b) explore the effects of trade tariffs on American companies' performance, showing that companies with complex, outsourced supply bases suffered more during the US–China trade war. Pan and Lei (2023) examine the increase in cash holdings among manufacturing firms due to trade frictions. However, these studies focus primarily on performance metrics and financial strategies, without exploring broader operational adjustments or alternative strategies, such as adjusting sourcing or entering new markets, which could help firms better navigate political risks.

Concerning strategic adjustments, Roscoe et al. (2022) identify eight decision-making logics based on interviews with SC executives, providing insights into redesigning SCs in response to geopolitical disruptions. While useful, the study lacks practical guidance on implementing these strategies, particularly in areas like SC diversification or technological adoption. Dong and Kouvelis (2020) propose a responsive newsvendor model for dealing with tariff increases but focus narrowly on short-term cost management without addressing the long-term strategic changes required to adapt to political uncertainty, such as nearshoring or SC reconfiguration. Hansen, Mena, and Aktas (2019) examine the offshore service industry, highlighting the impact of institutional and regulatory factors on outsourcing decisions but neglecting other political risks, such as corruption or social unrest, which also influence outsourcing dynamics.

Regarding government interventions, Lee and Yang (2024) discusses the role of government subsidies in stabilizing essential goods SCs during disruptions like the COVID-19 pandemic or the US–China trade war. While the study emphasizes the importance of government intervention, it assumes that subsidies will always be effective, ignoring potential inefficiencies or political resistance. Moktadir and Ren (2024) explores resilience challenges in the semiconductor SC, suggesting that strategies like regional manufacturing and supplier diversification can mitigate the impact of geopolitical tensions. While these recommendations are valuable, the study overemphasizes technological solutions like Research and Development (R&D) investment and does not fully address the political factors, such as trade barriers, that disrupt SCs.

The reviewed studies offer valuable insights into how political uncertainty affects SC operations but have notable limitations. Many focus narrowly on financial metrics and overlook broader strategic responses, such as SC diversification, nearshoring, or exploring new markets. Additionally, research on SC risk due to political uncertainty, particularly from trade frictions, remains in its early stages, with limited industry-based quantitative studies. Future research should develop a comprehensive framework that incorporates these strategies and considers a broader range of political risks beyond regulatory factors, providing a more nuanced understanding of how firms manage instability.

Building on the literature reviewed in the previous sections, we propose a multi-layer sequential BN conceptual model to assess SC risks. This model aims to provide a structured framework for evaluating the interdependencies and dynamics of risks within complex SC systems. To identify the primary risks within the context of the CCSC, we employ LDA thematic modeling. This approach enables us to extract key risk themes from a large data set, ensuring that the identified risks are both relevant and comprehensive. Furthermore, we conduct a simulation evaluation to assess the survivability of the CCSC under the specific conditions of the US–China trade friction. This simulation helps illustrate how these identified risks manifest in practice and provides valuable insights into the resilience of CCSCs in the face of geopolitical disruptions. The findings from this study will contribute to a deeper understanding of risk dynamics in global SCs and offer practical recommendations for improving risk management strategies in a politically uncertain environment.

3 Methodologies

3.1 Latent Dirichlet Allocation

The LDA model, proposed by Blei et al. (2003), is a probabilistic generative topic model designed to extract topics from documents. It is an unsupervised learning model that relies on word associations to identify relevant vocabulary within each topic. The LDA model, also referred to as a Bayesian probability model, comprises three layers: words, topics, and documents (Blei et al., 2003), with its specific model illustrated in Fig. 1.

To better illustrate the principles of the LDA model, let's assume a corpus $D = \{d_1, d_2, ..., d_N\}$ with N documents, where document d_n has M words and is represented as $d_n = w_{n1}, w_{n2}, ..., w_{nM}$, with each word $w_{nm} (m \in [1, M])$ being an entry in the vocabulary. The LDA model outlines the process of generating each word w_{nm} in document d_n in the following two steps, and Fig. 1 shows the specific process.

Step 1: For each theme $k \in [1, K]$

a) Sample a word distribution $\vec{\phi}_k \sim Dir(\vec{\beta})$

Step 2: For each document $d_n, n \in [1, N]$

a) Sample a topic distribution $\vec{\theta}_n \sim Dir(\vec{\alpha})$

b) For each word $w_{nm}, m \in [1, M]$ in the document d_n

i. Sample a theme $z_{nm} \sim Mult(\vec{\theta}_n)$

ii. Sample a word $w_{nm} \sim Mult(\vec{\phi}_{z_{nm}})$

In reality, the corpora are known, and our task is to deduce the document-topic distribution $\vec{\theta}_n$ and the topic-word distribution $\vec{\phi}_k$ of the corpus based on existing text data. Usually, this process can be performed using variational inference algorithms (Blei et al., 2003) or Gibbs sampling algorithms (Porteous et al., 2008). Our research uses the Gibbs sampling algorithm to obtain the global topic distribution and theme word distribution. For a specific word v, it can be concluded that:

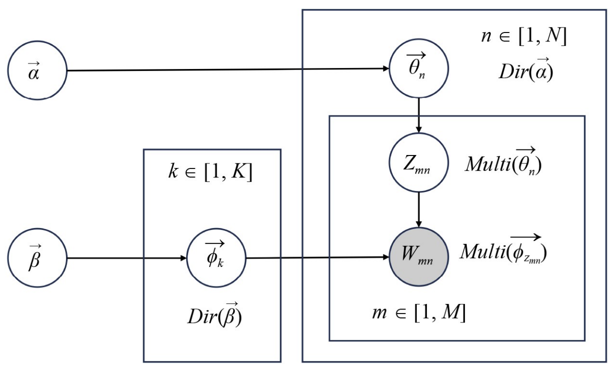


Fig. 1 Principle of LDA model.

$$\varphi_{k,v} = \frac{n_k^{(v)} + \beta_v}{\sum_{v=1}^{V} n_k^{(v)} + \beta_v}, \tag{1}$$

$$\theta_{n,k} = \frac{n_n^{(k)} + \alpha_k}{\sum_{k=1}^{K} n_n^{(k)} + \alpha_k}, \tag{2}$$

where $n_n^{(k)}$ represents the frequency of words belonging to topic k in document n, while $n_k^{(v)}$ represents the frequency of word v appearing in topic k. By applying Eqs. (1) and (2), we can calculate the Bayesian estimate of the posterior distributions for $\vec{\theta}_n$ and $\vec{\phi}_k$.

3.2 Bayesian network

The Bayesian network (BN), also known as the Bayesian belief network, is a multivariate knowledge visualization and probabilistic knowledge representation and inference model that was first formally proposed by Pearl in 1988. In comparison to other decision models, BNs exhibit a powerful capability to address uncertainties. They utilize conditional probabilities to depict relationships between elements and can learn and reason under conditions of limited and uncertain information. Furthermore, they can integrate prior knowledge and newly acquired information into the network, thereby enabling effective expression and fusion of multi-source information.

A BN is visually represented by a directed acyclic graph (DAG), comprising nodes (variables) and arcs (edges) that depict dependencies or causal relationships among the variables. To formally represent the structure of a BN mathematically, we consider a DAG denoted as G, where $G = (V, E)$, with $V = \{X_1, X_2, \ldots, X_n\}$ representing a set of random variables and E denoting a set of edges. The causal link between X_j and X_i is indicated by the edge that connects them, where X_j acts as the parent node of X_i, and X_i serves as the child node of X_j. This implies that the probability of X_i occurring is contingent upon the occurrence of X_j. The Conditional Probability Table (CPT) can be utilized to quantify the causal relationship between the child nodes and parent nodes. More broadly, if a BN consists of n nodes, $X_1, X_2, \ldots, X_n$, the joint probability distribution with independent conditions for each node variable, is presented below. Among them, $\pi(X_i)$ represents the parent nodes of X_i

$$P(X_1, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | \pi(X_i)). \tag{3}$$

The process of calculating the probability of node X_i being in state a_k after receiving evidence information is referred to as forward propagation analysis, also known as predictive inference. Its calculation formula is shown in Eq. (4)

$$P(X_i = a_k) = \sum_{X_i = a_k} P(X_1, \ldots, X_n). \tag{4}$$

The process of knowing the state of a node and obtaining the posterior probability distribution of its parent node based on the Bayesian theorem is referred to as backward propagation analysis, also known as diagnostic inference. If the state of X_i is known to be a_k, the posterior probability of node X_j (where X_j is a parent node of X_i) exhibiting a certain state is calculated as follows

$$P(X_j|X_i = a_k) = \frac{P(X_i = a_k|X_j)P(X_j)}{P(X_i = a_k)}. \tag{5}$$

To illustrate the implementation of BN, let's consider a simple BN. With the support of extensive news data, we identified that chip design risk (D) is primarily influenced by two risk factors: IP authorization interruption (I) and EDA software outage (E). Through the expert elicitation method, we collected assessment data on the possibility of these two risks and their consequences. We then used a risk rating matrix to convert this data into corresponding risk levels, which were used as the data set for the BN learning process (the more details about how to collect the data can be referred to Section 6.1). As a result, we obtain the known prior probabilities of high(H), medium(M), and low(L) levels of IP authorization interruption risk are 62.5%, 33.3%, and 4.17% respectively, while the prior probabilities of H, M, and L levels of EDA software outage risk are 75.0%, 20.8%, and 4.17%. Table 1 presents the conditional probability of design risk for these two risk factors. By applying Eq. (6), we can calculate the marginal probability, which yields 51.6% when the level of design risk is H.

$$\begin{aligned} P(D = H) = {} & \textstyle\sum_{I,E} P(D = H|I, E) \times P(I) \times P(E) \\ & = P(D = H|I = L, E = L) \times P(I = L) \\ & \times P(E = L) + P(D = H|I = L, E = M) \\ & \times P(I = L) \times P(E = M) + \dots \\ & + P(D = H|I = H, E = M) \\ & \times P(I = H) \times P(E = M) \\ & + P(D = H|I = H, E = H) \times P(I = H) \\ & \times P(E = H) = (0.333 \times 0.0417 \times 0.0417) \\ & + \dots + (0.625 \times 0.625 \times 0.75) = 51.6\%. \end{aligned} \tag{6}$$

Assuming that evidence information '$P(I = H) = 100\%$' is received and forward propagation analysis is conducted, the probability of a H-level of the design risk is 58.7%. The calculation process is shown in Eq. (7)

$$\begin{aligned} P(D = H) = {} & \textstyle\sum_{D=H} P(I, E, D) = (0.333 \times 0 \times 0.0417) \\ & + \dots + (0.333 \times 1 \times 0.0417) \\ & + (0.500 \times 1 \times 0.208) \\ & + (0.625 \times 1 \times 0.75) = 58.7\%. \end{aligned} \tag{7}$$

If the risk level of design risk is known to be H, the posterior probability of the risk level of node I being high is 71.1%, as demonstrated in Eq. (8)

$$\begin{aligned} & P(I = H|D = H) = \frac{P(D = H|I = H)P(I = H)}{P(D = H)} \\ & = \frac{(0.333 \times 0.0417 + 0.5 \times 0.208 + 0.625 \times 0.75) \times 0.625}{(0.3333 \times 0.0417 \times 0.0417 + \dots + 0.625 \times 0.75 \times 0.625)} \\ & = 71.1\%. \end{aligned} \tag{8}$$

4 The improved BN model

The methods employed in BN modeling primarily consist of expert knowledge and machine learning algorithms (Koller and Friedman, 2009; Rodgers and Singham, 2020; Ojha et al., 2018). Machine learning algorithms determine causal relationships (dependencies) between variables through data-driven learning (Hosseini and Ivanov, 2020). Broadly speaking, structural learning encompasses score-based and constraint-based approaches (Conrady and Jouffe, 2015). Notably, in scenarios with limited data or low data quality, data learning may result in overfitting or inaccurate structures. Moreover, discovering the optimal BN structure poses an NP-hard problem, characterized by a complex and time-consuming search process that easily falls into local optima.

To streamline the process of BN modeling, Hosseini and Ivanov (2022) proposed a multi-layered BN approach for modeling SC disruptions following the COVID-19 pandemic. Based on the applicability of expert knowledge and data, this approach facilitates the proficient modeling of SC disruptions within the pandemic milieu. The model comprises three layers: the first layer represents the interrupt triggering factor, the second layer includes risk events, and the third layer includes the consequences of disruptions.

However, the limitations of this model lie in its ability to solely focus on the impact of a specific activity, such as COVID-19, on all aspects of SC risks. SC risk is a

Table 1 CPT of 'Design Risk' node

IP authorization interruption	*L*			*M*			*H*		
EDA software outage	*L*	*M*	*H*	*L*	*M*	*H*	*L*	*M*	*H*
L	0.333	0.333	0.333	0.333	0.167	0.143	0.333	0.250	0.063
M	0.333	0.333	0.333	0.333	0.503	0.429	0.333	0.250	0.313
H	0.333	0.333	0.333	0.333	0.333	0.429	0.333	0.500	0.625

complex outcome influenced by multiple factors, and the SC itself comprises various hierarchical levels. The propagation of SC risk continuously spreads downstream along the SC network. Consequently, modeling solely the risk triggers and subsequent consequences falls short of providing a comprehensive assessment of SC risk across the entire industry. Building upon Hosseini and Ivanov (2022), this article proposes an alternative approach for risk modeling. By incorporating the sequential relationships of the SC into a multi-layer BN model, a novel multi-layer sequential BN model is introduced. Its objective is to evaluate the impact of risks propagating along the SC network on the risk of SC disruption.

As shown in Fig. 2, our model encompasses three layers that capture the risks associated with the upstream, midstream, and downstream of SC. The first layer encompasses a series of upstream risks (e.g. the disruption of raw material supply), which support the operation of the SC. The second layer consists of risks in the manufacturing process in the midstream (e.g. design or production risk). The third layer includes downstream risks in the SC (mainly risks of application), taking chips industry as an example, it mainly captures the risk of chip supply disruptions in industrial products, consumer electronics, and other terminal devices. The arrows represent the causal relationship among the three layers.

The conceptual model proposed in this paper can be used to assess, mitigate, and monitor the SC risks, ensuring the stable operation of the SC in uncertain environments, and minimizing potential losses caused by disruptions. Given that complex product SC consists of multiple continuous processes, it is advisable to employ sequential methods for evaluating and managing risks in various stages, which allows for more comprehensive and detailed risk management within the SC.

5 Risks in the chips supply chain

Our research takes the Chinese chip industry as the research target and focuses on the systemic damage caused by trade frictions. With trade tensions between the US and China as the backdrop, numerous Chinese chip companies have faced US sanctions, resulting in a shortage of chip supply, which has forced the production and innovation of downstream applications of CCSC such as industrial products and consumer electronics to stagnate. This situation has sparked concerns about chip SC security in China and globally.

We employ LDA thematic analysis to analyze mass media articles about the risks associated with CCSC. As mentioned above, the thematic model is a statistical model that uses algorithms for semantic analysis and clustering on the corpus to discover text themes and perform unsupervised classification (Papadimitriou et al., 2000). Because the thematic analysis is not constrained by any specific theories or methods (Sodhi and Tang, 2018), it is more suitable for exploratory research.

Our analysis utilizes the LDA method in the Python 3.9.12 environment. First, the crawled news corpus is preprocessed, which includes filtering and tokenization. Then the LDA algorithm is applied for analysis, and the

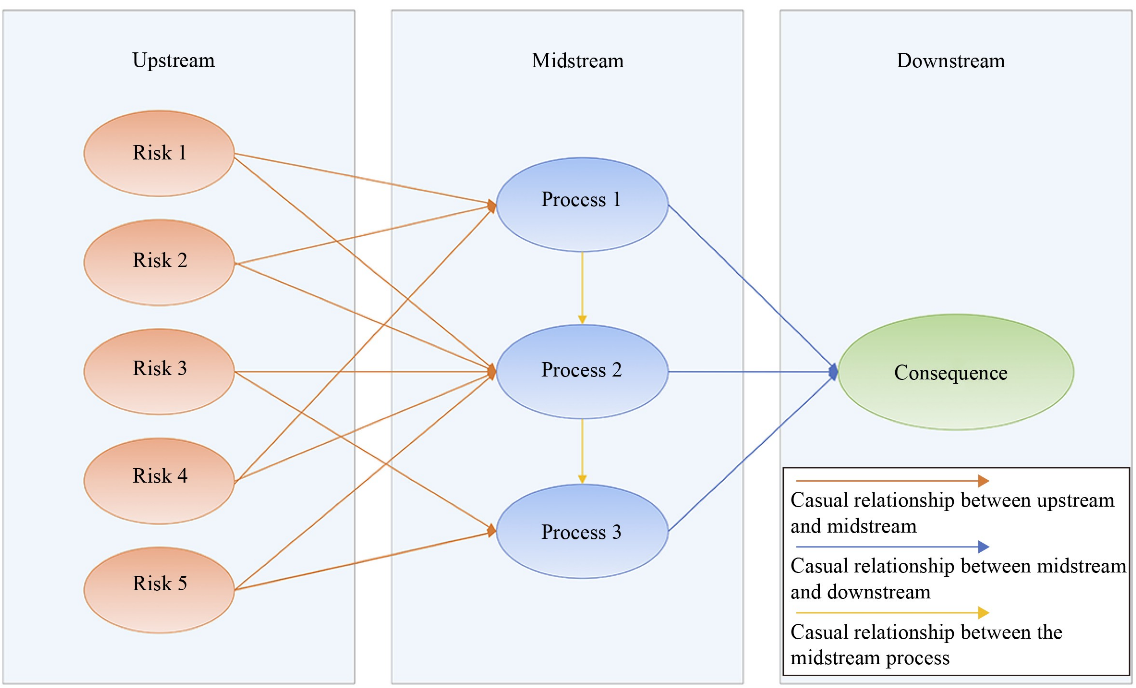


Fig. 2 The conceptual BN model for measuring SC disruption risk.

optimal number of themes is determined through perplexity. Following that, the clustering results are visualized, and theme classification is achieved by integrating the distribution of topics with the semantic analysis of words, ultimately leading to the creation of the thematic model.

To eliminate cross-linguistic influence and provide a focused analysis of the risk factors associated with CCSC, we primarily rely on Chinese news reports. Specifically, we conduct a comprehensive crawl of articles from NetEase News, a highly regarded online commercial medium in China. Our search utilizes specific keywords such as ‘semiconductor supply chain’, ‘semiconductor’, ‘chip supply chain’, ‘semiconductor supply chain risk’, ‘chip supply chain risk’, and ‘chip risk’ to cover the period from August 14, 2022, to August 14, 2023. Initially, a total of 437 news reports were collected; after removing duplicates, we selected 320 relevant articles (see Electronic Supplementary Material, Table S1). Through thorough theme analysis (specific LDA analysis results can be found in Electronic Supplementary Material, Table S2), we successfully developed the thematic model proposed in Section 5.1.

5.1 The causal thematic model of risk in Chinese chip supply chain

We summarized our causal thematic model (Fig. 3) from the LDA analysis result. The trade frictions primarily manifest in the supply cut-off of technology, components, talent, and raw materials. Among them, the technological disruptions include restrictions on EDA software, IP licensing, and certain imported equipment (such as lithography machines). Component disruptions mainly manifest as limitations on Chinese firms acquiring

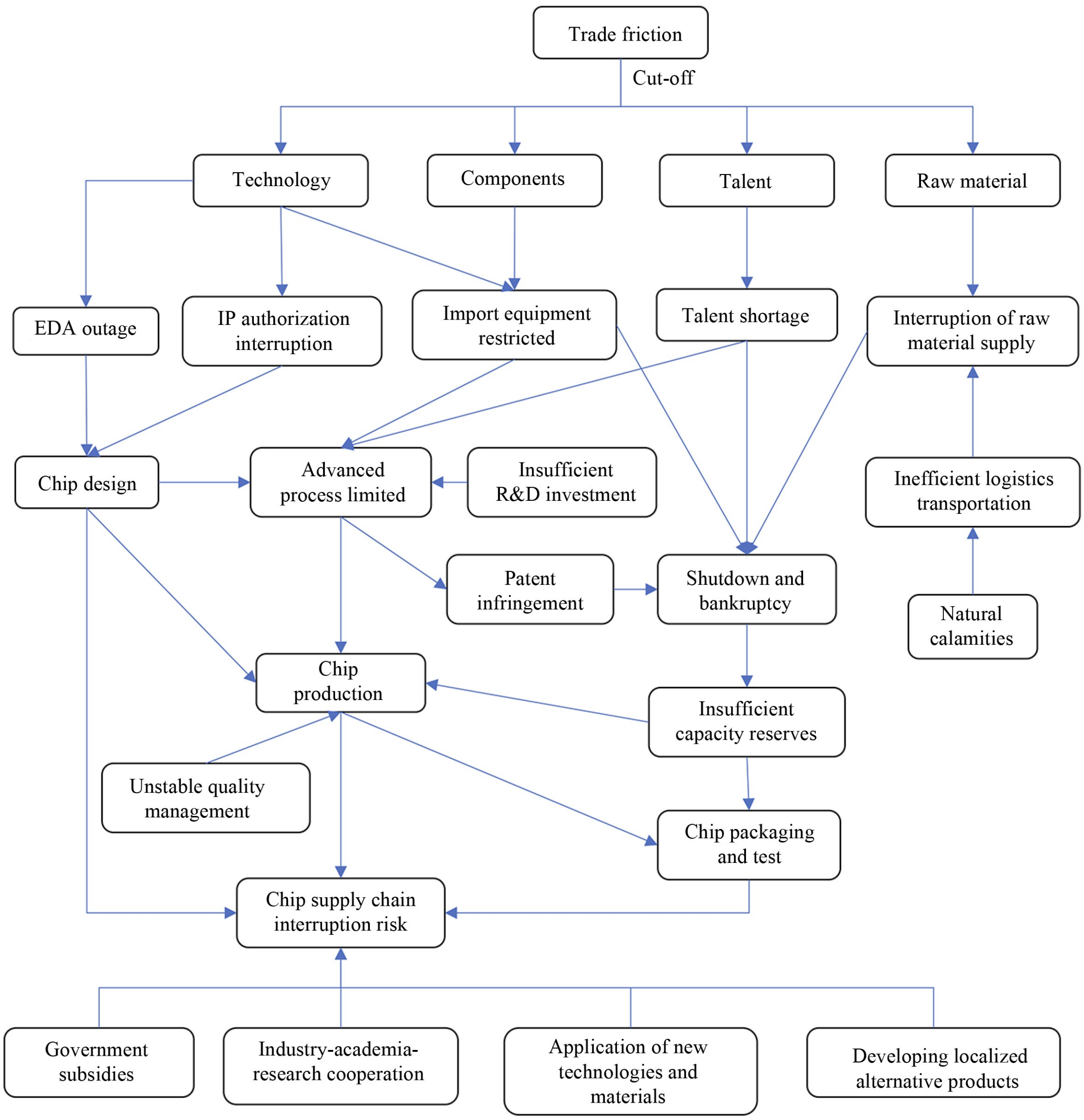


Fig. 3 The causal thematic model of risk in CCSC.

advanced chip manufacturing equipment and procuring necessary components for production and maintenance. Talent shortages stem primarily from the intensified competition for high-end chip talents between China and the US. Raw materials disruptions mainly involve silicon wafers, photoresists, and other aspects required for chip production. The multidimensional disruptions caused by trade frictions have had a significant impact on the upstream, midstream, and downstream of CCSC.

In the field of chip design, disruptions in EDA software and IP authorization due to the supply cut-off of technical pose huge risks to the design stage of CCSC. EDA software is the backbone of chip design. The US boasts a majority of EDA software suppliers, including Cadence Design Systems and Synopsys, while China's EDA software development lags. Restricting the export of EDA software would hinder the design, simulation, and verification capabilities of Chinese chip companies, thus constraining product development and innovation. Intellectual property core (IP core) refers to a circuit module design within a chip that possesses independent functions and is mature and reusable. Enterprises can purchase IP core that meets their specific needs and only design the creative and self-developed parts of the chip. The interruption of IP authorization significantly amplifies the R&D challenges faced by Chinese companies.

The supply disruptions triggered by trade frictions will also restrict imported equipment and exacerbate talent shortages. These two factors, combined with insufficient R&D investment and various obstacles encountered in the chip design process, will jointly lead to restrictions on the advanced chip R&D processes of sanctioned enterprises. At the same time, in the pursuit of catching up on technology, chip companies may encounter patent infringement issues, such as the intellectual property disputes between Taiwan Semiconductor Manufacturing Company (TSMC) and Semiconductor Manufacturing International Corporation (SMIC). From 2003 to 2009, TSMC filed four lawsuits against SMIC for alleged 'trade secret infringement'. Eventually, both parties reached an out-of-court settlement, with SMIC paying a substantial amount of compensation and its founder, Richard Chang, resigning due to the incident. Due to the combined impact of these factors, chip companies are at high risk of shutdowns or bankruptcies, resulting in inadequate capacity reserves across various stages of chip manufacturing such as production, packaging, and testing. This significantly escalates the risk of disruptions in the chip SC.

Apart from trade frictions, various factors in SC management can disrupt the stable operation of chip SC, including inefficient logistics transportation due to natural calamities (including epidemic lockdowns) that may affect the supply of chip raw materials. Moreover, unstable quality management during the production process can significantly impact the chip yield rate. The chip manufacturing process entails a sequential execution of distinct stages encompassing design, production, packaging and testing. Any risks present in the preceding stages can reverberate into the subsequent stages, and hinder their progress.

The LDA analysis also reveals a range of measures implemented by the Chinese government and enterprises to mitigate chip SC risks and address industry bottlenecks. These measures include bolstering policy support and providing financial subsidies to the chip industry, encouraging enterprises to invest in high-end R&D, enhancing innovation capabilities, and breaking down the technological barriers in Europe and America. Additionally, the government guides and encourages enterprises to strengthen international cooperation, introduce foreign technology, and utilize platforms such as the Belt and Road and Regional Comprehensive Economic Partnership (RCEP) to actively seek strategic cooperation with chip powerhouses like Japan, South Korea, and other regions or countries. Chinese enterprises are dedicated to developing localized alternative products to improve core competitiveness, and upgrading the industry through the utilization of new materials like silicon carbide and gallium arsenide, as well as emerging technologies like artificial intelligence.

In the following section, we will summarize the risk factors in the CCSC based on the findings of the LDA thematic analysis.

5.2 Chip supply chain risk factors

As depicted in Fig. 4, the CCSC comprises upstream supporting stage (e.g., EDA software, equipment, and semiconductor materials), midstream manufacturing stage (chip design, production, packaging, and testing), and downstream application stage (e.g., industrial products, consumer electronics, and computer related products). Drawing upon the findings of the thematic analysis, we can summarize several risk factors that may be encountered in the supporting stages of CCSC.

5.2.1 IP authorization interruption

Chip design is inseparable from advanced architecture and instruction sets, and the critical phase in the architectural process is selecting and configuring the appropriate IP core. On December 14, 2022, ARM, the world's largest chip IP licensing service provider, announced that it will no longer sell advanced CPU chip design IPs to Chinese companies (Tewari and Josephs, 2023). With the influence of Moore's Law, companies such as ARM and Intel continue to upgrade chip architecture. This restriction further exacerbates the situation for Chinese chip companies that face challenges in obtaining the most advanced chip architectures. Consequently, this puts them at risk of falling behind in new product development and facing potential elimination.

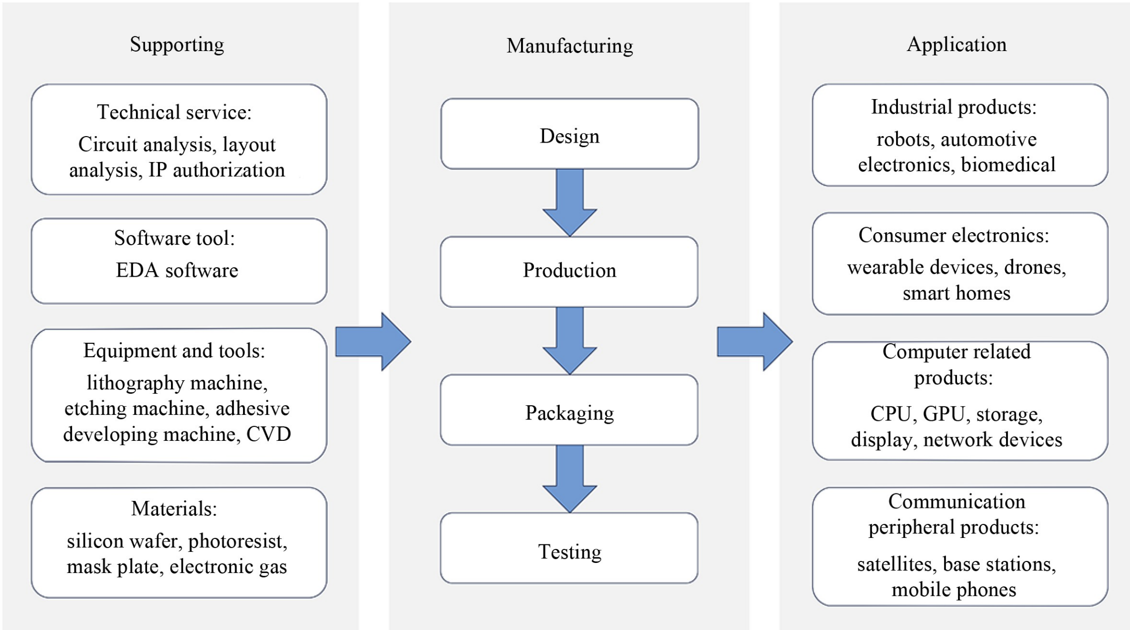


Fig. 4 Panorama of Chinese chip supply chain.

5.2.2 EDA software outage

In May 2019, the US government ruled that Huawei could not use American EDA software. In August 2022, the US Department of Commerce officially decided to ban the sale of EDA software to China (Yang, 2022). According to statistics, over 95% of the EDA software used by Chinese chip companies relies on imports from the US. R&D of EDA software in China is relatively backward, and there's a significant gap between its progress and that of leading tools that already support 5nm advanced technology.

5.2.3 Insufficient capacity reserves

Influenced by COVID-19, rising prices of raw materials, trade frictions, and intra-industry competition, a large number of chip factories have shut down or even gone bankrupt due to insufficient capacity reserves, resulting in a global chip shortage that has persisted since 2020. For CCSC, the situation is even more urgent. Insufficient capacity reserves for chip manufacturing have led to price fluctuations and an imbalance between supply and demand in the chip market, affecting over 169 industries. The automotive industry has been particularly affected, with many automakers having to suspend certain business operations (Fusion Worldwide, 2021).

5.2.4 Insufficient R&D investment

Insufficient investment in R&D may lead to adverse effects such as talent loss, insufficient industry innovation, and widening technology gaps. In 2022, global semiconductor companies invested over $90 billion in R&D, with the top five revenue-generating companies collectively investing $51.042 billion. In contrast, the top five chip companies in mainland China had a total R&D investment of only $1.953 billion (Beyond Consulting, 2023). Compared to leading enterprises, Chinese chip companies have relatively lower investment in R&D, resulting in insufficient support for technological innovation and product development.

5.2.5 Unstable quality management

Quality issues with chip raw materials, manufacturing equipment, or finished chip products can have various impacts. On the lighter side, it can affect customer impressions, while on the more severe side, it may result in customer losses and even damage the industry's reputation. Currently, tight production capacity has resulted in unstable quality, posing a major challenge to the stable operation of chip companies. For instance, on February 15, 2019, defects in the photoresist quality led to the scrapping and reworking of 100,000 wafers at TSMC, affecting six major customers including Apple, Qualcomm, NVIDIA, AMD, Hisense, and MediaTek, resulting in a revenue decline of approximately 550 million dollars in the first quarter (TSMC, 2019).

5.2.6 Talent shortage

Yang Deren, a distinguished Academician from the Chinese Academy of Sciences, has previously highlighted that the growth of the Chinese semiconductor industry comes up against substantial hurdles. These include a notable shortage of professional talent, constraints within training platforms, extended training durations, and relatively low compensation for practitioners (SemiInsights, 2021). According to the latest report on the *Supply and Demand of Talents in China's mainland's Integrated Circuit Industry in 2023*, the number of employees in China's integrated circuit industry in 2022 was 692,000. Taking into account the turnover rate, there is still a talent demand gap of approximately 35,000 people (Beyond Consulting, 2023). The talent shortage in the chip semiconductor industry will be a key bottleneck restricting its development.

5.2.7 Interruption of raw material supply

Interruptions in the supply of raw materials can result in delays in chip production. For instance, during the US–China trade war in 2018, the US imposed higher export tariffs on key raw materials like silicon and reactor tubes, which indirectly triggered a shortage of wafers in China in the third quarter of 2019 (Fusion Worldwide, 2021). Furthermore, if manufacturers are compelled to resort to unfamiliar suppliers or substitute materials, there may be quality management issues or differences in performance. Many crucial raw materials in Chinese chip manufacturing still rely on imports, including silicon wafers and photoresists, significantly amplifying the vulnerability of CCSC.

5.2.8 Advanced process limitation

In August 2022, *the Chip and Science Act* prohibited companies receiving subsidies from the US government from investing or expanding advanced process chips below 14nm in specific countries deemed as threats to the US. Furthermore, semiconductor companies that establish factories in the US will be ineligible for subsidies if they simultaneously build or expand advanced semiconductor manufacturing facilities in those specific countries (Tewari and Josephs, 2023). This has created a challenging situation for enterprises like TSMC and Samsung, which have semiconductor factories in both China and the US. These restrictions have made it difficult for chip manufacturers in mainland China to expand their production capabilities and continue their advancement toward advanced manufacturing processes.

5.2.9 Patent infringement

Patent infringement poses numerous obstacles to enterprise development. If a company is found to have infringed upon the patent rights of other companies, the defendant may face prolonged legal proceedings and substantial compensation. This not only consumes a significant amount of time and resources but also has a detrimental impact on the company's reputation, placing a significant burden on its cash flow and financial condition. Furthermore, it may restrict the company's ability to freely utilize certain technologies or intellectual property rights, thereby hindering innovation and impeding overall growth.

5.2.10 Import equipment restriction

In 2022, the US Department of Commerce imposed a requirement on all US chip production equipment manufacturers, prohibiting the export of production equipment for chips of 14nm or less to China, indicating that the export control to China was extended to semiconductor manufacturing equipment (Tewari and Josephs, 2022; Miller, 2022). This restriction not only hindered the chip manufacturing process of Chinese enterprises such as SMIC in the China's mainland but also affected the foundry factories such as TSMC operating in the China's mainland. Subsequently, relevant restrictions have been extended from production equipment to the installation and maintenance areas. For instance, suppliers are now prohibited from providing follow-up services for equipment already exported to China, making it more challenging for Chinese companies to increase their chip production capacity and innovate in the future.

5.3 The development of the BN model for measuring disruption risk of the Chinese chip supply chain

Based on the BN conceptual model proposed in the previous section, along with the insights from the panoramic view of CCSC (Fig. 4), the causal thematic model (Fig. 3), and the analysis results of chip SC risk factors, we develop the BN model for assessing the risk of CCSC, as shown in Fig. 5.

The upstream, midstream, and downstream in the BN conceptual model correspond to the supporting stage, manufacturing stage, and application stage of the chip industry chain respectively. The risk nodes in the upstream supporting stage correspond to several risk factors analyzed and summarized in Section 5.2. To analyze SC risks from a more macro perspective, our study assumes the independence of each risk factor in the supporting stage. The midstream manufacturing stage encompasses three main processes: chip design, chip production, and chip packaging and testing. Given that in practice, many companies, such as ASE group and China Wafer Level CSP Co. Ltd., integrate both the packaging process and the testing processes in chip manufacturing, this research treats them as a unified process. Our study primarily focuses on measuring the risk of chip SC disruption. Thus, the downstream application stage of the BN model only considers one target node, which is 'supply chain disruption'.

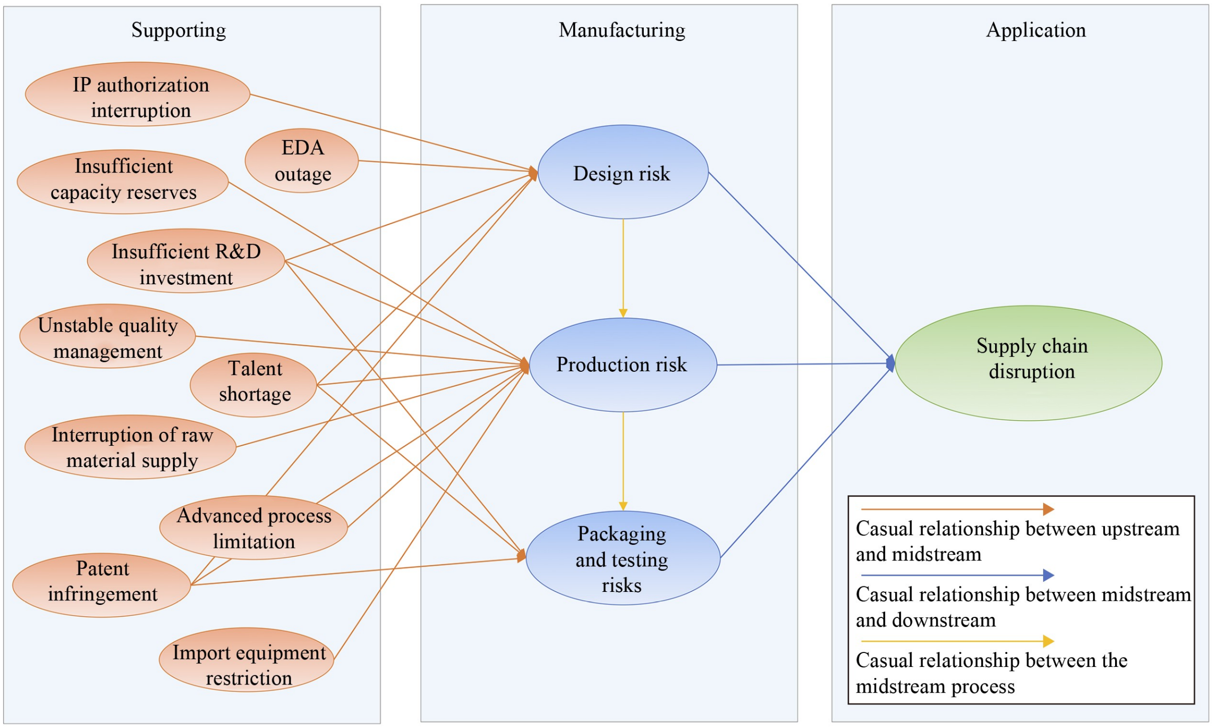


Fig. 5 The BN model for measuring CCSC risk.

6 Simulation results and analysis

6.1 Preliminary simulation results

In this subsection, we will explain the application of the BN model proposed in this study.

Step 1: Data acquisition

This study collected research data through expert elicitation. To ensure the scientific rigor and practical relevance of the survey, we conducted an extensive review of relevant literature to develop a systematic understanding of the chip industry. Additionally, we carried out preliminary research at companies such as SMIC, Jingjia Micro, Huawei, and Topway to refine the questionnaire design. During the formal survey, we distributed targeted questionnaires to gather insights from chip industry experts. The respondents came from a wide range of sectors, including enterprises, universities, and research institutions, such as ZTE Microelectronics, Jingjia Micro, SMIC, Fuman Electronics, and the School of Computer Science at Central South University. Their expertise spans multiple aspects of the chip supply chain, including raw materials, design, and manufacturing. The respondents' work experience ranged from 1 to 15 years, with more than 50% holding senior professional titles.

In sum, we surveyed 21 experts. There is no fixed minimum number of experts required for the assessment process, as it can vary from 3 to 20, depending on their experience and knowledge level in the given field (Dey, 2010; Sharma and Kumar, 2015). Therefore, it can be considered that a sufficient number of experts were allocated for this task in our case.

Step 2: Data conversion

The risk matrix is an effective tool used to visualize and prioritize risks (Cox, 2008; NPSA, 2008). It consists of the possibility (or probability or frequency) and consequence (or severity or impact) axes, used to estimate risk ratings.

This study employed a 5×5 risk level matrix (refer to Fig. 6) to convert the survey-based risk measurement results. The risk level matrix translates expert assessments of influence and likelihood for each risk factor into corre-

Likelihood \ Impact	1		Impact		5
5	M	M	H	H	H
	M	M	M	H	H
	L	M	M	M	H
	L	L	M	M	M
1	L	L	L	M	M

Fig. 6 Risk matrix.

sponding risk levels. Additionally, for midstream and downstream nodes, their risk levels are determined by averaging the influence and likelihood values of their parent nodes. Following this conversion process, the risk measurement results we obtain from the survey transform into a data set comprising high (H), medium (M), and low (L) risk levels, which provides crucial data support for subsequent BN parameter learning.

Step 3: Simulation results

Our study utilizes Netica, a software tool for probability reasoning and BN analysis, to conduct numerical simulations. The transformed data set is employed as the training set to learn the parameters of the BN. Through simulation, the results shown in Fig. 7 were obtained. The simulation result shows that due to a series of unstable factors such as trade friction and COVID-19, the probability of CCSC being at high disruption risk is 35.1%, the probability of being at medium disruption risk is 36.5%, and the probability of being at low disruption risk is 28.4%.

6.2 Sensitivity analysis

A useful approach to evaluate the effectiveness of expertly built models is by conducting sensitivity analysis, which provides a clear understanding of the variables (nodes) that exert the most significant influence on the target node (Fenton and Neil, 2018). For sensitivity analysis, we focus on 'supply chain disruption' as the target variable and assess the influence of risk factors on it through conditional probability measurements. Specifically, we examine the gap between $P(S=H|R=H)$ and $P(S=H|R=L)$, where S represents the risk status of the final node and R denotes the status of the risk factors.

Figure 8(a) illustrates the results of the sensitivity analysis of the node 'chip supply chain disruption' at risk level H, under the influence of various risk factors. The length of each bar in the tornado chart represents the degree to which each risk factor impacts the target node. For example, when the risk level of talent shortage is high (H), the probability of CCSC disruption being H is 0.365. Conversely, when the risk level of talent shortage is low (L), the probability of disruption in CCSC being H is 0.339. The sensitivity analysis demonstrates that talent shortage, patent infringement, and insufficient investment in R&D are the three most significant factors influencing the disruption of the CCSC, with their significance ranked in descending order. Figures 8(b) and 8(c) represent the analysis results of 'supply chain disruption' at risk levels M and L, given the same set of risk factors.

6.3 Propagation analysis

When we update the probabilities of each node in a BN by inputting observation values, it is referred to as propagation. A unique feature of the BN network is that we can input observations at any node and use propagation to update the marginal probabilities of all unobserved variables (Fenton and Neil, 2018). Typically, there exist two main types of propagation: forward propagation and backward propagation (Hosseini and Ivanov, 2022). Forward propagation is a reasoning process from cause to effect, where the cause variable is updated, and the marginal probability of the affected variable is measured. In contrast, backward propagation is a reasoning process from result to cause, where inputting observation results in the 'result' node will be utilized to correct the probability distribution of the 'cause' node.

6.3.1 Forward propagation analysis

Forward propagation is employed to monitor the spread of changes in the level of risk nodes. When there is compelling evidence of an observation, it can be incorporated into the model, leading to the updating of probabilities

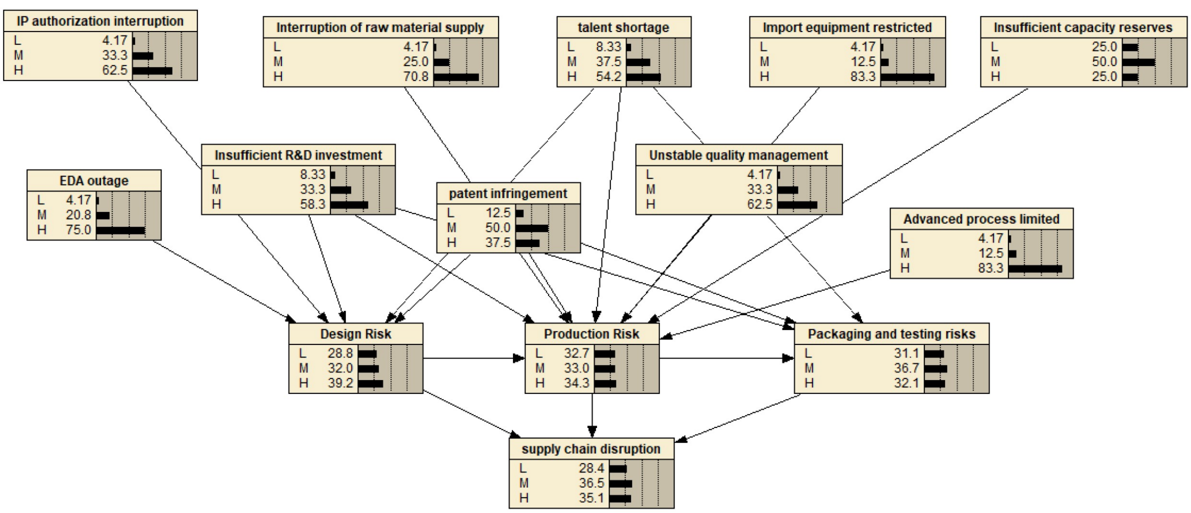
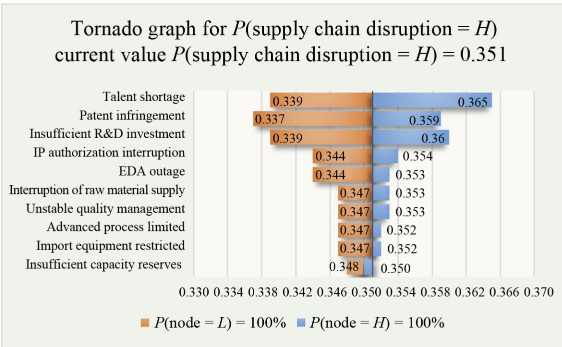
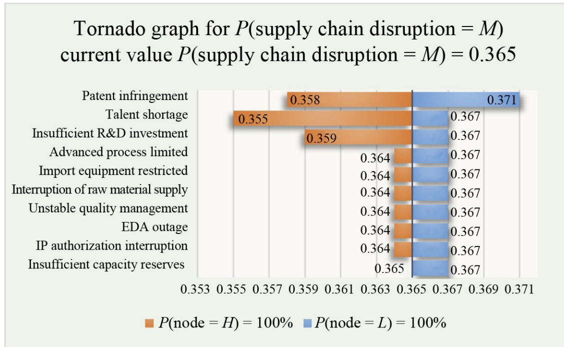


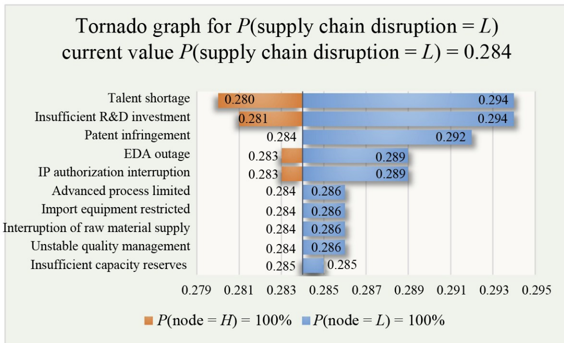
Fig. 7 Simulation results.



(a) P(supply chain disruption = H) = 100%



(b) P(supply chain disruption = M) = 100%



(c) P(supply chain disruption = L) = 100%

Fig. 8 Tornado graph displaying the impact of risk factors on SC disruption.

for all unobserved variables.

After analyzing the theme model results, we can outline a series of mitigation measures implemented by the Chinese government and enterprises to mitigate chip SC risks and tackle chip bottleneck issues. These measures comprise: i) strengthening policy support and financial subsidies for the chip industry by the government, ii) carrying out industry–academia–research cooperation with economies possessing leading chip industries, iii) developing localized alternatives, and iv) applying new techniques and materials to achieve industrial upgrading. Thus, we create four distinct forward propagation scenarios based on these mitigation strategies, which are demonstrated in Table 2. The third column in the table represents the primary nodes affected by each scenario, with their risk levels designated as L, and the fourth column represents the probability that the risk level of node 'supply chain disruption' is rated as H in each scenario.

The first scenario refers to increasing government subsidies. With government support, enterprises can enhance their R&D investment and improve talent incentives, thereby mitigating the talent shortage issue. They can also allocate more funds toward measures like expanding production capacity through increased production equipment and emergency procurement. In this case, the probability of SC disruption with a risk level of H decreases from 35.1% to 33.6%. The second scenario focuses on promoting industry–university–research cooperation. Through collaborations with more leading economies in the chip industry, companies can alleviate talent shortages, obtain licenses for precision equipment procurement, and gain patent authorizations. These actions help alleviate the crisis of limited advanced processes. Consequently, the probability of a chip SC disruption with a risk level of H decreases from 35.1% to 33.8%. The third scenario involves the application of new technologies and materials. By innovating in technology and materials, enterprises can alleviate the risks arising from restrictions on imported equipment, interruptions in raw material supply, limitations in advanced processes, and patent infringement risks to varying degrees. As a result, the probability of SC disruption with a risk level of H decreases from 35.1% to 33.8%. The fourth scenario is to develop localized products. Currently, many Chinese companies are dedicated to developing EDA software, advanced chip architectures, and precision manufacturing equipment such as lithography machines. This effort helps circumvent the limitations imposed by advanced processes, leading to a reduction in the probability of a chip SC disruption with a risk level of H from 35.1% to 34.1%.

Through forward propagation analysis, the effectiveness of four measures in mitigating risks in CCSC can be compared, among which the measure of increasing government subsidies has been found to have the greatest mitigating effect. The reason for this is that the chip industry has the characteristics of being capital,

Table 2 Four scenarios of forward propagation analysis and the updated probability of the final node

No	Scenario	Affected nodes (level: *L*)	Probability
1	Government subsidies	Insufficient R&D investment, Talent shortage, Insufficient capacity reserves	0.336
2	Industry–University–Research cooperation	Patent infringement, Advanced processes limited, Imported equipment restricted	0.338
3	Developing localized alternative products	EDA outrage, IP authorization interruption, Imported equipment restricted, Advanced processes limited	0.341
4	Applying new technologies and materials	Imported equipment restricted, Interruption of raw material supply, Advanced processes limited, Patent infringement	0.338

technology, and talent intensive, requiring significant capital investment and sustained R&D innovation. Government subsidies play an indispensable role by providing financial support, promoting the competitiveness of domestic enterprises, and attracting more investors to participate in the industry. Additionally, when companies receive increased financial support through government subsidies, they can further facilitate collaboration between industry, academia, and research institutions, fostering the development of localized alternative products, and the application of new technologies and materials (scenarios 2–4).

6.3.2 Backward propagation analysis

The capability of performing backward propagation analysis is a distinctive feature of BN to input observation values at target nodes and update the marginal probability of unobserved variables. To conduct backward propagation analysis, we set the risk level of chip SC disruption to *H* and update the risk probability of upstream risk factors and midstream manufacturing processes. Since SC disruption is directly affected by the three process nodes of design, production, packaging, and testing in the midstream manufacturing process, we focus on the probability changes of these three parent nodes when the risk level of chip SC disruption is *H*.

Backward propagation analysis reveals that in this worst-case scenario, the probability of the risk level of *H* in the chip design process, production process, and packaging and testing process increases from 39.2%, 34.3%, and 32.1% of the basic model to 47.2%, 44.3%, and 35.7%, respectively (as shown in Fig. 9). The results indicate that when the risk of the chip design process, production process, and packaging and testing process increases to these critical values, it will lead to a high disruption risk in the 'supply chain disruption' node of the downstream application end of CCSC. Therefore, it is vital for managers to regularly evaluate risks across all processes of the chip SC and take important risk mitigation measures for nodes that closely approach the critical risk values, to ensure the stable operation of the chip SC.

By comparing the critical values of the midstream manufacturing process in the basic model and backward propagation analysis, it is evident that the risk in the CCSC packaging and testing process is approaching a critical level. With the rapid development of the chip industry in China's mainland in recent years, the chip packing and testing processes have experienced significant growth due to its low technical barriers and labor-intensive nature. Currently, the global seal test industry basically presents a situation of tripartite confrontation between the US, China's mainland, and China's. However, following the US-China trade friction, numerous Chinese chip manufacturers represented by Huawei HiSilicon, have gradually transferred their chip test orders to the test manufacturers in the China's mainland, resulting in the full capacity utilization of leading test manufacturers such as JCET Group Co., Ltd. Furthermore, the advancement of semiconductor applications has brought forth higher requirements for chip packaging and testing processes. While traditional packaging technology primarily focuses on chip protection, advanced packaging technology requires a delicate balance between chip performance factors such as power consumption, heat dissipation, and data processing. Consequently, the packing and testing process is faced with substantial risks associated with technological changes.

In response to this situation, enterprises can implement several measures to alleviate the risk, such as increasing R&D investment to promote innovative development, optimizing production processes to enhance efficiency, strategically planning orders to ensure optimal resource utilization, and considering investments in building additional factories to expand production capacity.

6.4 Resilience and importance analysis

Resilience has always been a crucial indicator in SC risk-related research, with scholars extensively exploring the definitions and quantification methods for it (Cheng et al., 2022; Saisridhar et al., 2024). Additionally, by assessing the importance of risk nodes, we can pinpoint the key nodes impacting the SC disruption risk. Analyzing node resilience and importance enhances our understanding of the severity of risk events within the CCSC discussed here, offering valuable insights for risk mitigation strategies in resource-constrained scenarios.

We define resilience $\mathfrak{R}$ as the ability of the SC to maintain system performance during a risk event, measured by the

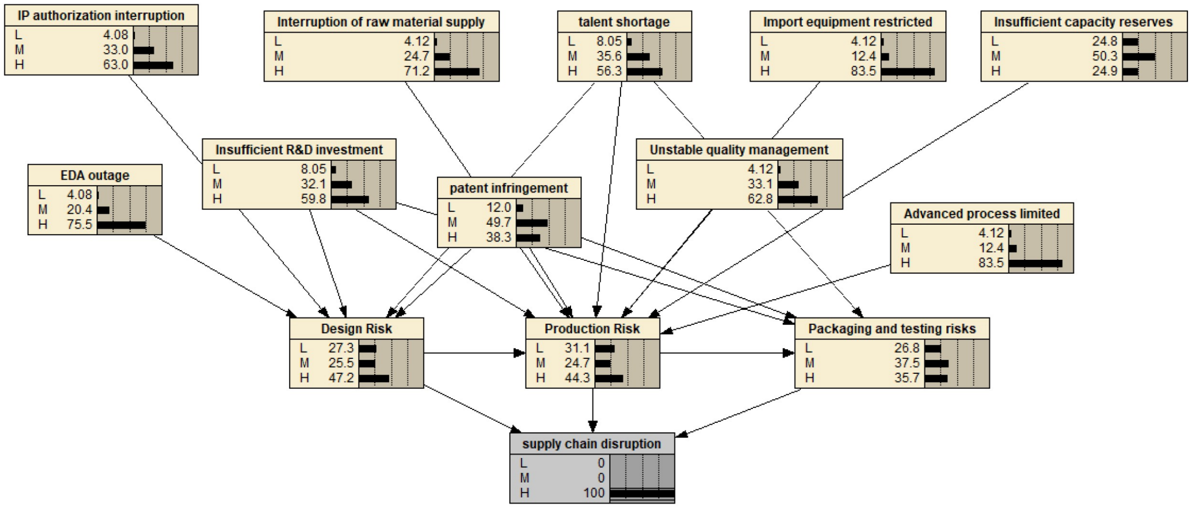


Fig. 9 The backward propagation analysis result.

change in probability of the ‘supply chain disruption’ node being at a high-risk level. Specifically, we measure the resilience of the node by observing how the probability of the ‘supply chain disruption’ node being in a high-risk state change when a risk event shifts from a normal state to a high-risk state. If this change in the event’s state causes a sharp increase in the probability of the ‘supply chain disruption’ node being in a high-risk state, it indicates that the node has low resilience to the event.

$$\Re = 1 - \frac{P(S = H|R = H) - P(S = H|G)}{P(S = H|R = H) - P(S = H|R = L)} = 1 - \frac{\alpha}{\beta}. \quad (9)$$

In the above formula, S stands for the risk status of the ‘supply chain disruption’ node, while R denotes the risk status of the risk node in upstream, and $P(S = H|G)$ represents the baseline probability of the node of ‘supply chain disruption’ being at a high-risk level under normal conditions (current situation). Meanwhile, $P(S = H|R = L)$ and $P(S = H|R = H)$ signify the probabilities of the node of ‘supply chain disruption’ in a high-risk level when the risk nodes in the upstream are in a low-risk and high-risk level, respectively. α reflects the change in the probability of ‘supply chain disruption’ being in a high-risk level when the level of risk node transitions from the current level to a high-risk level, while β denotes the overall range of probability change for the node of ‘supply chain disruption’ in the high-risk level. The larger the value of α/β, the lower the ability of the SC system to resist changes in node risk levels, indicating lower resilience.

Inspired by sensitivity analysis, we define the importance I of each risk node as the change in probability of the ‘supply chain disruption’ node being at a high-risk level when the upstream node is in a different risk level. This definition reflects how sensitive the node of ‘supply chain disruption’ is to changes in the risk state of upstream nodes. The greater the change in probability, the more important the upstream risk node is in determining the overall risk of supply chain disruption.

$$\mathrm{I} = P(S = H|R = H) - P(S = H|R = L). \quad (10)$$

The calculation results are shown in Table 3. We quantified the calculation results of resilience and importance as percentages, which is convenient for comparing the relative resilience and relative importance of each risk node examined in our research.

We visualize the calculation results in Fig. 10. The three risk nodes of ‘talent shortage’, ‘insufficient R&D investment’, and ‘patent infringement’ are located in the (1) quadrant of Fig. 10, indicating that these are the three most important risk events in the CCSC examined in this research. At the same time, their resilience is low, that is, the ability of the CCSC to resist the risk of system disruption caused by these risk events is relatively low. Therefore, it is imperative to pay attention to these events, increase R&D investment in the CCSC, formulate talent-attracting policies to draw high-quality professionals into the chip industry, and enhance enterprise innovation capabilities. The (2) quadrant indicates that the risk nodes are important to the SC and have high resilience. Currently, there are no risk nodes that are located in this quadrant, indicating that resilience enhancement strategies for various risk events should be further strengthened. The risk nodes in the (3) quadrant include ‘EDA outrage’, ‘IP authorization interruption’, etc. These risk events have weaker resilience but less importance than the risk nodes in the (1) quadrant. Consequently, with limited resources, priority should be given to improving the resilience of the chip SC at the (1) quadrant nodes, followed by enhancing the resilience of the (3) quadrant nodes. The nodes located in quadrant (4) of the graph indicate a higher resilience to risk events and relatively lower importance.

Table 3 Calculation results of risk node resilience and importance

Node	Acronym	Resilience	Quantization(%)	Importance	Quantization(%)
Insufficient capacity reserves	CR	1.50	1.00	0.002	0.00
Import equipment restricted	ER	0.80	0.33	0.005	0.13
Advanced process limited	AP	0.80	0.33	0.005	0.13
Unstable quality management	QM	0.67	0.20	0.006	0.17
Interruption of raw material supply	RM	0.67	0.20	0.006	0.17
EDA outage	EDA	0.78	0.30	0.009	0.29
IP authorization interruption	IP	0.70	0.23	0.01	0.33
Insufficient R&D investment	R&D	0.57	0.11	0.021	0.79
patent infringement	PI	0.64	0.17	0.022	0.83
talent shortage	TS	0.46	0.00	0.026	1.00

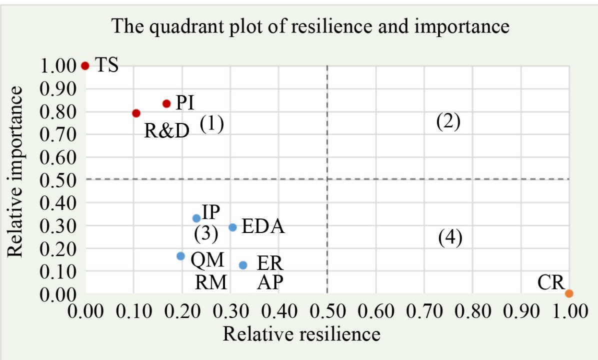


Fig. 10 The quadrant plot analysis of resilience and importance.

7 Theoretical and managerial insights

Trade frictions and the COVID-19 epidemic have intensified the fragility of SCs across different industries, particularly in the highly complex field of chip manufacturing, which heavily relies on global collaboration. Drawing from the findings of this study, several theoretical and managerial insights can be derived.

In theoretical terms, this study introduces a novel perspective on utilizing BN for modeling SC risk amid uncertain events. The combination of BN and LDA methods offers powerful decision support tools for identifying, modeling, and quantifying the impact of risk events on SC disruptions. This research advances the understanding of how uncertainty and risk propagation can be effectively captured in complex SC environments, providing a framework that can be applied to other industries experiencing similar risks.

In terms of management insights, managers can utilize the BN conceptual model proposed in this research to effectively model and quantify SC risks. By employing propagation analysis, they can simulate the effectiveness of various mitigation measures in reducing SC risks and obtain a deeper comprehension of the extent to which risk events and the risks during the manufacturing processes must be reduced in the event of potential disruptions, with the ultimate aim of enhancing SC performance.

Through our research on the risks within CCSC, we have pinpointed talent shortages, patent infringement, and inadequate R&D investment as the primary factors exerting the greatest impact and importance on the risk of disruptions within the SC. Concurrently, it has been revealed that the chip SC exhibits the least risk resilience concerning these factors. These results highlight the urgent need to strengthen the innovation capabilities of the Chinese chip industry. To ensure long-term stability and competitiveness, particularly amid the escalating geopolitical tensions and great-power competition, it is essential for industry practitioners to prioritize investments in cutting-edge technologies, foster innovation, and focus research efforts on core technologies that can reduce dependence on external markets. Furthermore, the evaluation of risk mitigation strategies underscores that augmenting government subsidies yields the most pronounced risk alleviation effect. This finding is particularly relevant to policymakers, as the capital-intensive nature of the chip industry requires substantial financial support for sustained R&D and technological development. Policymakers should consider expanding financial incentives and fostering a more favorable environment for innovation, helping domestic companies become more competitive and less vulnerable to external disruptions. Additionally, insights from backward propagation analysis also reveal that production transfers within the chip manufacturing process have led to the chip packaging and testing stages operating at full capacity, pushing risk probabilities to critical levels. This highlights the importance of scaling up the capacity of these processes. Industry practitioners should focus on enhancing the capacity and efficiency of packaging and testing operations, ensuring that these critical steps can handle increased demand and mitigate production bottlenecks.

8 Conclusions

Geopolitical tensions have drawn attention to the vulnerability of SC, particularly in high-tech industries. Unlike risks such as fire or earthquake which can cause instantaneous interruptions, political uncertainty poses a sporadic and unpredictable threat. Moreover, unlike localized disruptions caused by COVID-19, political uncertainty tends to target the industry as a whole, resulting in highly uncertain and destructive interruption risks.

In this study, we present a comprehensive multi-layer sequential BN conceptual model, designed to assess SC risk in the context of uncertain events such as trade frictions and the COVID-19 epidemic. Our model comprises three layers: risk factors, process risks, and disruption consequences. These layers enable us to capture risks at the upstream, midstream, and downstream processes of the SC. We utilize the LDA thematic modeling approach to identify risks within CCSC, summarize ten downstream risk factors, propose four risk mitigation measures and propose a BN model to measure the risk of CCSC. Using sensitivity analysis and propagation analysis, combined with perspectives on resilience and importance, we analyze and evaluate the various risk events and mitigation measures affecting CCSC in the context of the US–China trade conflict.

Sensitivity analysis reveals that talent shortage, patent infringement, and insufficient R&D investment are the three primary factors exerting a significant impact on the risk of disruption in CCSC. On the other hand, forward propagation analysis demonstrates that increasing government subsidies represents the most effective measure for mitigating risks in the current CCSC. This is due to the fact that government subsidies can effectively mitigate investment risks faced by chip enterprises, foster technological innovation and market promotion, optimize industrial structure, and enhance the overall competitiveness of the Chinese chip industry. Furthermore, backward propagation analysis offers a reliable method for monitoring the SC risks. By conducting backward propagation analysis, managers can determine the critical values associated with each node in a worst-case scenario. Managers can regularly evaluate the risks associated with each node in the SC, and if necessary, implement mitigation measures to ensure the stable operation of the entire SC. In addition, the analysis of the resilience and importance of CCSC risks reveals that talent shortage, insufficient R&D investment, and patent infringement are the most critical yet least resilient nodes in CCSC. Other risk events such as unstable quality management, EDA software outrage, and IP authorization interruption exhibit low resilience but are slightly less important than the aforementioned risk events. This underscores the urgent need to enhance innovation capability in CCSC. Priority should be given to investing resources in cultivating more high-quality talents, bolstering enterprise R&D efforts, and actively developing more patents.

From a managerial perspective, the insights from this study provide valuable guidance for industry decision-makers. The BN model offers a robust tool for identifying and quantifying risks, simulating the effectiveness of various mitigation strategies, and evaluating the resilience of SCs. Managers in the chip industry, and other sectors facing similar geopolitical and economic challenges, can use the proposed model to proactively manage risks, optimize resources, and ensure the long-term stability of their operations.

However, this research still has some limitations and offers potential avenues for future investigation. First, although the conceptual model we proposed has been used for chip SC risk assessment in the context of the US–China trade war, its universality allows for its application in assessing SC risks across various industries, including new energy and healthcare. At the same time, this paper solely focuses on a subset of risk factors that primarily impact the stable functioning of the chip SC. In future research, it would be worthwhile to examine additional types of risk factors, including but not limited to energy crises and economic collapses. Furthermore, this study primarily aims to investigate the most severe consequence of risk propagation, which is SC disruption. In future research, it would be beneficial to also consider other metrics, such as SC responsiveness and performance. Further research avenues could involve utilizing dynamic BN for risk modeling, enabling the assessment of temporal fluctuations in risk probabilities.

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