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DeepSeek-Assisted Dynamic Impact Monitoring System for Industrial Chain

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Abstract

In recent years, frequent emergencies such as the COVID-19 pandemic and regional conflicts have significantly heightened uncertainty risks in global industrial chains. Safeguarding industrial chains is crucial for sustaining national economic stability, and while major countries prioritize industrial chain security, establishing an effective industrial chain monitoring system remains a substantial challenge. This paper establishes a dynamic impact monitoring system (DIMS), which can dynamically monitor the risk level of the industrial chain. The DIMS consists of an industrial chain static risk assessment model (IC-SRAM) and an industrial chain dynamic event monitoring model (IC-DEMM). The IC-SRAM is used to evaluate the risks of the industrial chain itself, and the IC-DEMM is used to monitor external risk events in real time. DeepSeek is used to associate events with industrial chain nodes. The dynamic industrial chain risk value is formed based on the results of static risk assessment and dynamic risk event monitoring. Finally, an empirical analysis of the new energy vehicle industrial chain is carried out. The results show the effectiveness of the proposed DIMS and the accuracy rate of associating industrial chain nodes using DeepSeek reaches 91%.

Keywords: deep learning; DeepSeek; dynamic monitoring; industrial chain risk; TOPSIS

1. Introduction

In recent years, the COVID-19 pandemic, earthquakes, wars, and other emergencies have occurred frequently, and the risk of uncertainty in the global industrial chain has increased sharply [1,2]. The industrial chain risks are not isolated events but are embedded in a broader polycrisis context, in which climate change, geopolitical tensions, trade and tariff wars, and public-health emergencies coexist and mutually amplify one another [3]. The supply chain disruption has a serious negative impact on customers and suppliers, and can lead to the failure of the entire supply chain [4–7]. For instance, geopolitical frictions have triggered export controls on critical minerals [8] and climate-induced disasters have disrupted raw-material supply. All major countries attach great importance to the safety of the industrial chain. Preventing the risks of the industrial chain and maintaining the stability of the industrial chain is the key to maintaining the stable development of the national economy. Industrial chain security risk monitoring can accurately identify the risk points of the industrial chain, dynamically track the risk situation of the industrial chain, and help the national and local governments prevent and resolve the risks of the industrial chain. However, it is a challenge to establish an effective industrial chain risk monitoring system.

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The literature on industrial chain and supply chain risk reveals two streams. The first stream concerns static risk and resilience assessment of industrial chains and supply chains. Okabe and Ohtani [9] constructed a risk model for evaluating the risks involved in industrial safety. Li et al. [10] established a two-dimensional evaluation index system to evaluate the comprehensive trade risks of countries for each node of the industrial chain. The industrial chain nodes are aggregated from different HS codes. Levner and Ptuskin [11] focused on environmental risks in supply chains and presented an entropy-based optimization model to evaluate the economic loss caused by the environmental risks subject to the ripple effect. Wu et al. [12] constructed a coal industrial chain resilience evaluation indicator system. The Interval Type-2 Fuzzy Prospect Theory and TOPSIS method are used for evaluating the resilience level of the coal industrial chain. It used subjective scoring methods to score the overall coal industrial chain and calculate the resilience of the coal industrial chain in Shaanxi Province. Based on the mineral industrial chain security characteristics, Lin et al. [13] used the substance flow analysis method to construct an integrated evaluation system for the whole life cycle of China's indium industrial chain. Hua et al. [14] utilized financial data to propose an industrial chain risk assessment and early warning model that combined Hierarchical Graph neural network and Long Short-Term Memory. Huang et al. [15] calculated the tail risks of China's petrochemical energy, traditional manufacturing, emerging manufacturing, and agriculture and consumption industrial chain based on stock index returns. Index-based studies [9,10,12,13] quantify vulnerability along selected dimensions but treat the chain as an aggregate whole or rely on coarse HS-code granularity, thereby failing to localize risk at the product-level node. Optimization and substance-flow models [11,13] improve rigor yet remain static and data-intensive, while recent data-driven early-warning systems [14,15] depend on financial or stock-market signals that respond only belatedly to operational disruptions. Reviews of supply chain resilience [1,2] and recent studies of cascading failures in supply networks [16] similarly observe that most assessment and propagation modeling is conducted at the firm or network level, with little node-level resolution, and that vulnerability and capability are rarely linked to real-time external events. The shared shortcoming is that static assessment alone cannot capture how an exogenous shock amplifies the risk exposure of a specific node.

The second stream addresses dynamic risk monitoring through sensors or textual data. In terms of dynamic risk monitoring of the industrial chain, Tian et al. [17] established a practical industrial risk monitoring system based on the wireless sensor network. The system used special inspection robots to monitor the environmental and safety risk factors in the industrial environment, which improves the resilience of the respective industrial operations. Ganesh and Kalpana [18] proposed a model for analyzing social media data to identify potential supply chain risks in real-time. The model used the Twitter streaming API to retrieve information from online SC forums. The results show that potential risk factors can be obtained from the recent data by text-mining analyses. Through the monitoring of news data, the potential risks of the industrial chain can be perceived in real time. Keyword- and sensor-based monitoring [17,18] and the deep-learning identification of industrial chain disruption events [19] improved over manual screening, but event-to-node association still depends on manually curated keyword or virtual-node libraries, which fail to capture implicit, industry-specific semantics. Natural-language models such as TextCNN, fastText, BERT, and ERNIE [20–28] advanced text classification, and text-mining and large-language-model methods are increasingly applied to supply chain risk identification from news [29]. Deep-learning frameworks now predict supply chain risks across critical industries [30], and detect disruptions through system-dynamics and deep-learning hybrids [31]. Agentic and LLM-grounded frameworks monitor supply chain disruptions from news and map them to multi-tier networks [32,33]. However, these works either stop at detecting risk events, focus on firm- or network-level disruption propagation, or associate events through lexical or graph retrieval, and the semantic association of risk events with fine-grained industrial chain nodes via a large model remains under-explored. The advanced semantic comprehension capabilities of large language models, such as DeepSeek [34], enable precise identification of industry-specific terminology and implicit information within headlines. It facilitates the critical task of associating risk events with relevant supply chain nodes.

Across the two streams, they share two common limitations. First, most studies treat the industrial chain as an aggregate whole or rely on coarse product granularity, so they cannot pinpoint risk at the level of specific nodes and cannot be updated in real time as the external environment changes. Second, where dynamic monitoring exists, it depends on manually curated keyword libraries or sentiment heuristics that miss implicit, industry-specific semantics and therefore suffer from low association accuracy between risk events and chain nodes. These gaps directly motivate the following research questions: (1) How can the static vulnerability of individual industrial chain nodes be quantified in a comparable and objective manner? (2) How can external risk events be identified, classified, and associated with the correct chain nodes automatically and in real time? (3) How should static vulnerability and dynamic impact be integrated to yield a dynamic risk index that is both interpretable and responsive?

To address these questions, this paper aims to establish a dynamic impact monitoring system (DIMS) that couples an industrial chain static risk assessment model (IC-SRAM) with an industrial chain dynamic event monitoring model (IC-DEMM). The IC-SRAM answers question (1) by quantifying node-level vulnerability through an objective entropy-weighted TOPSIS on six indicators across three dimensions; the IC-DEMM answers question (2) by fine-tuning an ERNIE model to identify and classify risk events from news [19] and by employing DeepSeek to semantically associate events with chain nodes; the IC-DIMM answers question (3) by fusing static vulnerability and dynamic impact into a single dynamic risk index.

The innovations of this paper are as follows:

Firstly, a dynamic impact monitoring system (DIMS) for the industrial chain, including static risk assessment and dynamic risk monitoring, has been constructed. In terms of the industrial chain static risk assessment model (IC-SRAM), a universal industrial chain security risk assessment index system has been established for the assessment of static risks in the industrial chain. This system covers three dimensions: competitive strength, supply dependence, and market dependence, with a total of six indicators.

Secondly, the TOPSIS method is used to calculate the degree of security risk in each dimension of the industrial chain. Based on the characteristics of the risk assessment of the industrial chain, the positive and negative ideal solutions are set as absolute values to avoid amplification of the assessment risk. The relative closeness degree is used to represent the degree of risk in each dimension of the industrial chain.

Thirdly, an industrial chain dynamic event monitoring model (IC-DEMM) is established based on deep learning methods. It intelligently identifies and classifies industrial chain risk events from massive news data, and uses DeepSeek to associate risk events with industrial chain nodes.

Fourthly, integrate the IC-SRAM with the IC-DEMM to construct an industrial chain dynamic impact monitoring model (IC-DIMM). An industrial chain risk index is established for dynamic monitoring of the risk level of the industrial chain and its nodes. Taking the new energy vehicle industrial chain as an example for empirical analysis, the effectiveness of the model was verified.

2. Model

2.1. Dynamic Impact Monitoring System

The DIMS of the industrial chain consists of an IC-SRAM and an IC-DEMM, as shown in Figure 1. The IC-SRAM is used to evaluate the risks of the industrial chain itself, while the IC-DEMM is used to track and monitor external risk events in real time. Self-risk refers to the current situation of risks in an industrial chain, such as technological gaps, weak high-end manufacturing capabilities, weak market expansion capabilities, and weak ecological control capabilities, which are reflected in the external dependence of each industrial chain node. Within a certain period of time, the inherent risks of the industrial chain are relatively stable, and it is necessary to continuously improve the security level of the industrial chain through industrial development. The IC-DEMM is used to monitor external impact events such as markets, policies, and disasters in real time. External risks change frequently, and some events can directly impact the weaknesses of the industrial chain and transmit them to the entire industrial chain, causing huge impacts and losses to the entire industrial chain.

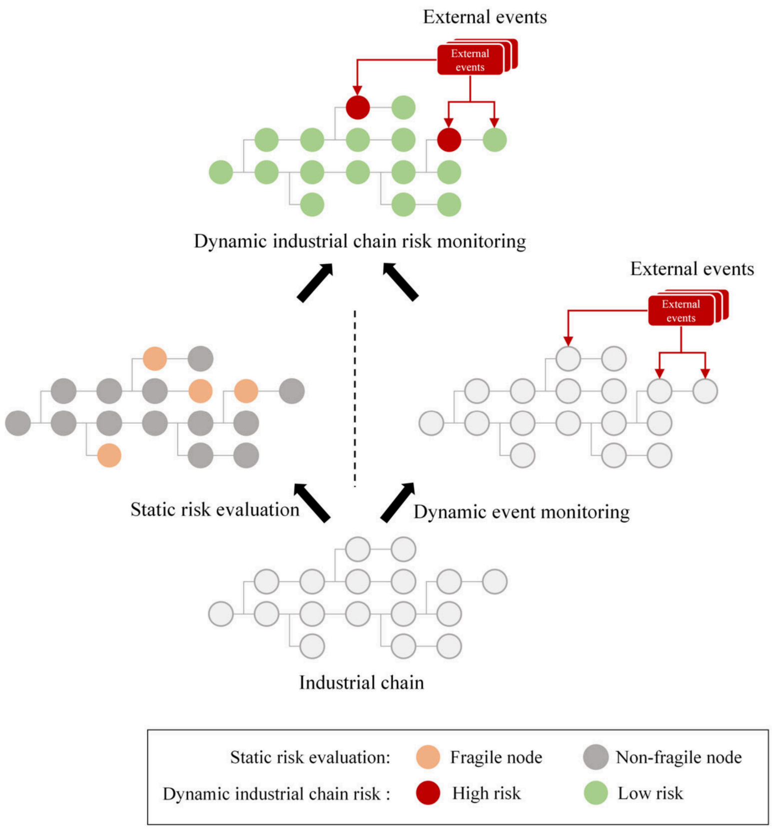

Figure 1. The architecture of a dynamic impact monitoring system for the industrial chain.

The IC-SRAM describes the current situation of the nodes in the industrial chain. Under normal circumstances, the risk level of industrial chain nodes does not affect the normal operation of the industrial chain. It only represents whether the node is fragile and susceptible to external events. If a node in the industrial chain is fragile, the impact of external events on that node will be significant. If a node in the industrial chain is not fragile, the impact of external events on that node is relatively small.

2.2. Industrial Chain Static Risk Assessment Model

2.2.1. Indicator System

The industrial chain is a chain composed of different segmented industries, with nodes that are segmented to the product level. Traditional indicators for industry evaluation, such as labor productivity, trade competitiveness index, explicit comparative advantage index, and R&D investment intensity, are difficult to obtain and are no longer applicable to the IC-SRAM. The essence of industrial chain static risk assessment is to evaluate the fragility of the industrial chain, reflecting whether the industrial chain is susceptible to external risk shocks and resulting in losses. Considering the dimensions of industrial security assessment, the evaluation dimensions of industrial chain static risk assessment are set to three dimensions: competitive strength, supply dependence, and market dependence. Based on the principles of scientificity, systematicity, typicality, comparability, and operability, the specific indicators are selected as follows.

The three dimensions and six indicators are grounded in industrial security assessment principles: competitive strength, supply dependence, and market dependence capture the three channels through which an industrial chain node can be externally constrained, and they mirror the dimension structure adopted in related industrial-chain and trade-risk studies [10,12]. The indicators are operationalized through comparable ratios that are measurable at the product level, and the number of indicators is intentionally kept small to sustain interpretability and data availability across different chains.

The competitive strength measures the control and competitiveness of industrial chain nodes themselves, mainly from aspects such as external dependence of technology and the degree of control of foreign-funded enterprises; supply dependence measures the degree of import dependence risk at industrial chain nodes. For example, if there is a single source country for imports, there is a greater risk of supply. It is mainly measured from the external dependence of imported products and the concentration ratio of the imported product market; market dependence measures the degree of risk in the export market at industrial chain nodes. For example, if exports are concentrated in a single country, once a product cannot enter the market, the impact on the production and sales of that node will be transmitted upstream, thereby affecting the entire industrial chain. It is mainly measured from overseas market dependence and the concentration ratio of the export market.

2.2.2. Assessment Model Construction

The multi-criteria decision making (MCDM) method has been widely used in the evaluation of different industries [35]. Among many MCDM methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is one of the most popular evaluation methods [36]. It has achieved satisfactory results in different application fields [37–41]. This paper will also use the TOPSIS method to evaluate the static risk of the industrial chain. The selection of indicator weights is an important part of assessment models, and the entropy weight method is an objective method of calculating weights based on the information of indicator values [42]. A small entropy of an indicator indicates that it is important and therefore should have a higher weight [43]. The calculation steps for indicator weights under the first-level dimension are as follows:

(a) Given a set of industrial chain nodes, $A = \{a_1, a_2, \ldots, a_n\}$ represents a total of n industrial chain nodes to be evaluated. A set of first-level dimensions, $DM = \{dm_1, dm_2, \ldots, dm_z\}$, represents a total of z dimensions. A set of indicators, $B_z = \{b_{z,1}, b_{z,2}, \ldots, b_{z,m}\}$, represents a total of m indicators in the dm_z dimension. Given $x_{k,ij}, k = 1,2,\ldots,z, i = 1,2,\ldots,n, j = 1,2,\ldots,m$ as the evaluation value of indicator $b_{k,j}$ in industrial chain node a_i in the dm_k dimension, the entropy value of each indicator $e_{k,j}$ in the dm_k dimension is calculated as follows:

$$p_{k,ij} = \frac{x_{k,ij}}{\sum_{i=1}^{n} x_{k,ij}}, i = 1,2,\ldots,n, j = 1,2,\ldots,m \tag{1}$$

$$e_{k,j} = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{k,ij} \ln p_{k,ij}, j = 1, 2, \ldots, m \tag{2}$$

(b) Calculate the deviation value $d_{k,j}$ and weight $w_{k,j}$ of each indicator under the dm_k dimension.

$$d_{k,j} = 1 - e_{k,j}, j = 1, 2, \ldots, m \tag{3}$$

$$w_{k,j} = \frac{d_{k,j}}{\sum_{j=1}^{m} d_{k,j}}, j = 1, 2, \ldots, m \tag{4}$$

TOPSIS is a method of calculating the relative closeness of each solution based on its distance from positive and negative ideal solutions, and then ranking and comparing the solutions based on the magnitude of the relative closeness [35]. According to the TOPSIS calculation method, the evaluation value is directly generated by calculating the end-level indicator, surpassing the intermediate dimension [44]. Due to the need for risk calculation on the first-level dimension in this paper, the TOPSIS method has been modified to first calculate the risk value of the first-level dimension, and then synthesize the final risk value through the risk value of the first-level dimension. The specific calculation process is as follows:

(a) Given a set of industrial chain nodes, $A = \{a_1, a_2, \ldots, a_n\}$ represents a total of n industrial chain nodes to be evaluated. A set of first-level dimensions, $DM = \{dm_1, dm_2, \ldots, dm_z\}$, represents a total of z dimensions. A set of indicators, $B_z = \{b_{z,1}, b_{z,2}, \ldots, b_{z,m}\}$, represents a total of m indicators in the dm_z dimension. The weights of the dm_z dimensions $w_k = \{w_{k,1}, w_{k,2}, \ldots, w_{k,m}\}$, where $w_{k,j} \geq 0, j = 1, 2, \ldots, m$ and $\sum_{j=1}^{m} w_{k,j} = 1$. Given $x_{k,ij}, i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$ as the evaluation value of indicator $b_{k,j}$ in industrial chain node a_i in the dm_k dimension, the initial evaluation matrix of the first-level dimension can be obtained:

$$X_k = \begin{bmatrix} x_{k,11} & x_{k,12} & \cdots & x_{k,1m} \\ x_{k,21} & x_{k,22} & \cdots & x_{k,2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{k,n1} & x_{k,n2} & \cdots & x_{k,nm} \end{bmatrix} \tag{5}$$

(b) According to the definition of each indicator, the values of each indicator are between [0, 1], and there is no need for further standardization. Due to the particularity of industrial chain risk, some industrial chain nodes may have maximum values for all indicators. Adopting a relative ideal solution with the maximum and minimum values may amplify the degree of risk. To avoid amplification of risk, the positive ideal solution and negative ideal solution are fixed as a combination of 1 and 0, respectively. The weighted distance from the industrial chain node to the positive ideal solution and negative ideal solution is calculated in the dm_k dimension, and is represented by $s_{k,i}^{+}$ and $s_{k,i}^{-}$, respectively:

$$S_{k,i}^{+} = \sqrt{\sum_{j=1}^{m} w_{k,j}\left(x_{k,ij} - 1\right)^2}, i = 1, 2, \ldots, n \tag{6}$$

$$S_{k,i}^{-} = \sqrt{\sum_{j=1}^{m} w_{k,j}\left(x_{k,ij} - 0\right)^2}, i = 1, 2, \ldots, n \tag{7}$$

(c) Calculate the relative closeness (i.e., risk value) between the industrial chain node a_i and the positive ideal solution in the dm_k dimension:

$$C_{k,i}^{*} = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \ldots, n \tag{8}$$

(d) Taking the maximum risk value for each first-level dimension represents the static risk value of the industrial chain nodes. The higher the risk value, the higher the risk of the industrial chain node.

$$C_i^* = MAX\left(C_{1,i}^*, C_{2,i}^*, \ldots, C_{z,i}^*\right), i = 1, 2, \ldots, n \tag{9}$$

2.3. Industrial Chain Risk Event Monitoring Model

According to the nature of external events, the risks of the event can be divided into three categories: competition risk, supply risk, and market risk. The risk types correspond one-to-one to the first-level dimensions in the static risk assessment system. The IC-DEMM aims to identify risk events and event types based on news titles. Unlike the method of constructing a vocabulary library for industrial chain nodes described in [19], this paper employs the DeepSeek model to associate events with industrial chain nodes. By leveraging the semantic comprehension capabilities of large-scale models, the accuracy of event-node association within industrial chains can be enhanced.

The model construction process and risk event identification process are shown in Figure 2. Firstly, the collected news data is labeled with risks and risk types. Then, the ERNIE pre-training model is fine-tuned to establish an industrial chain risk event recognition model and an industrial chain risk event classification model, respectively. The complete workflow of the IC-DEMM involves sequential processing of monitored news data through three core components: the risk event identification model, the risk event classification model, and the DeepSeek model, ultimately generating risk events associated with each node in the industrial chain.

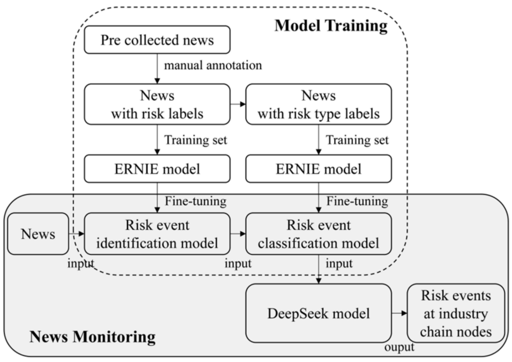

Figure 2. The construction process and risk event identification process of the IC-DEMM.

The ERNIE models were trained on the news-title dataset constructed in our prior work [15]. More than 20,000 news titles were collected from major Chinese financial and industrial media; each title was manually reviewed by domain experts and labeled as either a risk event or a risk-free event, yielding a labeled set of more than 600 industrial chain risk events. For the three-category classification task, each labeled risk event was further assigned to one of three risk types. The distribution of the labeled risk events was dominated by supply-risk events, with competition and market events forming the remainder. To form a balanced benchmark, 150 risk events (25%) and an equal number of risk-free events were randomly drawn as a test set, and the remainder served as the training set. Because the training set was class-imbalanced, an oversampling method was used, in which each risk-free event was randomly paired with a risk event to balance the two classes.

Both the identification and the classification models were built by adding a classifier layer on top of the ERNIE pre-trained model and fine-tuning on an NVIDIA T4 GPU. Following iterative optimization, the identification model reached an accuracy of 92% on the balanced test set, against only 31% for a sentiment-classification baseline [15]; the processing speed is about 500 news titles per second, and the model identifies roughly 1000 risk events per month from mass news.

Unlike the keyword-library approach in [15], the DeepSeek model [32] associates a risk event with the correct industrial chain node through semantic understanding rather than literal matching. The implementation calls the DeepSeek-V3 API with a structured prompt that (1) defines the role and task, (2) supplies the list of industrial chain nodes of the target chain, and (3) requires the model to return the single most relevant node. A representative prompt is given below.

> User: 'You are an industrial chain risk analyst. Given a risk event title and the list of nodes of a specified industrial chain, identify the single node most directly impacted by the event. If the event does not concern any node, return NA. Industrial chain nodes: lithium battery materials, high-temperature alloy, electric motor, batteries, IGBT, MCU, electric vehicle. Event: General Motors acknowledges EV production challenges constrained by battery supply. Return the impacted node.'

The model's semantic logic is to infer the implicit subject–object relationship in the title. Although the event mentions 'EV production ', the root cause lies in battery supply constraints. DeepSeek thus recognizes that the event directly concerns the batteries node rather than the electric vehicle node. This implicit-relationship reasoning is what keyword libraries cannot capture.

2.4. Dynamic Risks in the Industrial Chain

According to the DIMS, the final risk of the industrial chain consists of two parts: the IC-SRAM and the IC-DEMM. The multiplicative integration of static and dynamic hazards is motivated by the interaction mechanism through which a chain node is impacted. A node sustains meaningful dynamic risk only when it is both statically fragile and dynamically exposed, so static risk provides the susceptibility baseline while the standardized event count modulates it, keeping the final dynamic risk value within [0, 1]. The calculation process is shown below.

(a) Standardization. Standardize the static risk value of the industrial chain to the range of [0, 0.5]. Use $Q_{k,i}$ to represent the number of risk events of the kth risk type in the industrial chain node a_i, and standardize $Q_{k,i}$ to the range of [1, 2].

$$\widetilde{C}^*_{k,i} = C^*_{k,i}/2, i = 1, 2, \ldots, n \tag{10}$$

$$\widetilde{Q}_{k,i} = \frac{Q_{k,i} - \min_i}{\max_i - \min_i} + 1 \tag{11}$$

(b) Calculate the dynamic risk value R_i of the industrial chain node a_i, with a value range of [0, 1].

$$R_{k,i} = \widetilde{C}^*_{k,i} \cdot \widetilde{Q}_{k,i}, i = 1, 2, \ldots, n \tag{12}$$

$$R_i = MAX(R_{1,i}, R_{2,i}, \ldots, R_{z,i}), i = 1, 2, \ldots, n \tag{13}$$

3. Empirical Analysis

3.1. Experiments

The empirical study is conducted on the new energy vehicle industrial chain, a strategically important and rapidly evolving manufacturing sector. The division of the industrial chain can generally be divided into raw materials, components, production equipment, and finished products. This paper selects seven nodes from the new energy vehicle industrial chain as the monitoring objects, including lithium battery materials, high-temperature alloy, electric motor, batteries, IGBT, MCU, and electric vehicle.

Online news titles were continuously collected from major Chinese financial and industrial media from the second half of 2022 to 2024 as the data source for dynamic event monitoring. The ERNIE-based identification and classification models were deployed to process the monitored news, and the DeepSeek-V3 model was called through its API to associate each identified risk event with the corresponding industrial chain node. The static risk of each node was computed from the six indicators of Table 1 using the entropy weight and TOPSIS methods, and the dynamic risk index was obtained by fusing the static risk with the monitored dynamic events following Formulas (10)–(13). The overall experimental procedure follows the architecture of Figure 1 and the workflow of Figure 2.

Table 1. The indicator system of industrial chain static risk assessment.

First-Level Indicator	Second-Level Indicator	Remarks
Competitive strength (x_1)	External dependence of technology (x_{11})	Proportion of using foreign technology patents
	Degree of control of foreign-funded enterprises (x_{12})	Proportion of foreign and domestic enterprises in key enterprises
Supply dependence (x_2)	External dependence of imported products (x_{21})	Market share of foreign enterprises/total market share
	Concentration ratio of imported products (x_{22})	Market share of national enterprises with the highest proportion/market share of all foreign enterprises
Market dependence (x_3)	Overseas market dependence (x_{31})	Foreign market revenue/operating revenue
	Concentration ratio of export market (x_{32})	The highest proportion of national market revenue/total foreign market revenue

3.2. Results

The weight of each indicator can be obtained by Formulas (1)–(4). Using Formulas (5)–(10), the static risk of the first-level dimension of each node in the industrial chain can be calculated, and the overall static risk can be obtained. The results can be shown in Tables 2 and 3.

Table 2. The weight of the indicator system.

	x_{11}	x_{12}	x_{21}	x_{22}	x_{31}	x_{32}
Entropy	0.86	0.78	0.72	0.85	0.56	0.49
Deviation value	0.14	0.22	0.28	0.15	0.44	0.51
Entropy weight	0.08	0.13	0.16	0.09	0.25	0.29
Final weight	0.39	0.61	0.64	0.36	0.46	0.54

Table 3. The static risk of each node in the industrial chain.

Industrial Chain Node	$C^*_{1,i}$	$C^*_{2,i}$	$C^*_{3,i}$	C^*_i
Lithium battery materials	0.1126	0.1797	0.4763	0.4763
High-temperature alloy	0.5803	0.5634	0.1408	0.5803
Electric motor	0.3407	0.2393	0.3723	0.3723
Batteries	0.1459	0.0801	0.0862	0.1459
IGBT	0.6192	0.6781	0.0439	0.6781
MCU	0.6122	0.7211	0.0383	0.7211
Electric vehicle	0.2423	0.2213	0.0582	0.2423

Through monitoring of news from the second half of 2022 to 2024, a total of 3671 risk events in the new energy vehicle industrial chain were identified, of which the main type of risk was supply risk (2002), accounting for 55%. A part of the monitoring results is shown in Table 4. The changes in the three types of risk events are shown in Figure 3.

Table 4. A part of the monitoring results.

Industrial Chain Node	Risk Event	Risk Type
Batteries	One of the main lithium battery production bases in China, Ningde Shidai Sichuan Battery Factory, was shut down due to power restrictions	Supply event
MCU	Electronic Industry Weekly: The delivery time of NZP products continues to lengthen, and the supply of automobile chips remains in short supply	Supply event
Lithium battery materials	Polyfluoropoly: In the short term, lithium hexafluorophosphate and other materials still maintain a tight supply pattern	Supply event
Batteries	Rivian CEO: The battery shortage of electric vehicles may be more serious than the chip shortage	Supply event
Lithium battery materials	The supply gap of negative electrode material head enterprises may be around 300,000 tons this year	Supply event
Lithium battery materials	Top lithium suppliers warn that car companies will face fierce competition for lithium	Contest event
Lithium battery materials	Argus' analysis: Indonesia may impose export tariffs on nickel products	Contest event
Lithium battery materials	Canada requires three Chinese companies to divest lithium mine assets in Canada	Contest event
Batteries	BYD responded to the rumors that the United States has banned Chinese batteries: it is not prohibited, but there is no subsidy	Market event
Electric vehicle	Energy shortage: Switzerland may introduce a ban on the use of electric vehicles	Market event

Overall, the number of risk events was the highest in May 2024, with a total of 335. In December 2024, the number of risk events decreased to 116. Supply events were prevalent in the latter halves of both 2022 and 2023, while competitive and market events both increased during the latter half of 2024. After using the DeepSeek model to associate risk events with industrial chain nodes, the distribution of risk events at each industrial chain node is shown in Figure 4.

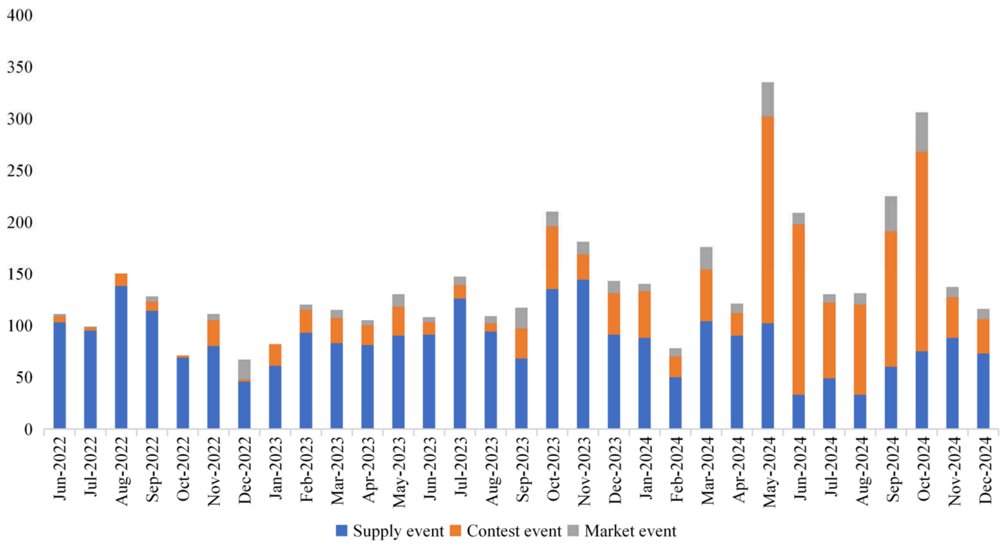

Figure 3. The changes in the three types of risk events.

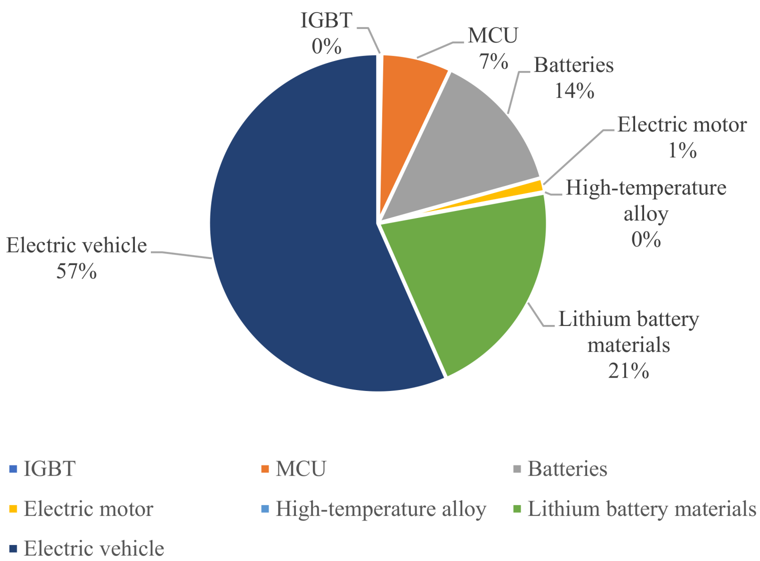

Figure 4. The distribution of risk events at each industrial chain node.

A random subset of 10% risk events underwent manual verification to compare the association accuracy between the vocabulary library-based model [19] and the DeepSeek model. Results indicate that the vocabulary library-based model achieved an accuracy rate of 82%, while the DeepSeek model attained 91%. The sample test data is shown in Table 5; the DeepSeek model demonstrates superior capability in analyzing and comprehending event semantics, thus enabling precise association with industrial chain nodes.

Among the verified subset, the DeepSeek model misassociated roughly 9% of the events. Inspection of these errors reveals three recurring patterns. (1) No-association events forced into a node. Some events are only tangentially related to the chain. The correct label is 'NA', but the model occasionally assigns the nearest topically related node. Errors are concentrated in genuinely ambiguous, weakly related events rather than in clearly node-specific ones. (2) Multi-node ambiguity. Events spanning several nodes are assigned to one node where several are defensible. (3) Implicit/indirect relationships. Events whose link to a node is mediated by an unstated industry convention are occasionally missed. These three patterns indicate that the main residual weakness concerns boundary cases with no clear single node. As the semantic understanding and reasoning capabilities of large language models continue to advance, their ability to handle complex scenarios is expected to grow steadily, making such mis-association issues increasingly manageable. In parallel, incorporating such boundary cases into the prompt design will further help refine the association accuracy.

Table 5. The sample test data for associating risk events with relevant supply chain nodes.

Risk Event	Incorrectly Associated Node (Vocabulary Library-Based Model)	Correctly Associated Node (DeepSeek Model)
Ford announces suspension of new EV battery plant construction	Electric Vehicle	Batteries
Manchin seeks revocation of U.S. Treasury exemptions for Chinese EV battery minerals	Electric Vehicle	Lithium Battery Materials
U.S. auto industry coalition urges White House to oppose Cleveland-Cliffs' acquisition of U.S. Steel	Electric Vehicle	NA
General Motors acknowledges EV production challenges constrained by battery supply	Electric Vehicle	Batteries
World Power Battery Conference highlights: Strengthening upstream raw material supply guarantees	Batteries	Lithium Battery Materials
U.S. implements new regulations disqualifying China-battery-equipped vehicles from tax credits	Electric Vehicle	Batteries
Identifying investment opportunities amid U.S. photovoltaic cell capacity shortages	Batteries	NA
Supply concerns intensify: LG Chem declares securing EV battery raw materials "top priority"	Batteries	Lithium Battery Materials
General Motors' EV production hampered by Ultium battery supply issues	Electric Vehicle	Batteries
Auto chip supply shortage persists with major manufacturers planning price increases	Electric Vehicle	MCU

The dynamic risk value of each node in the new energy vehicle industrial chain can be calculated using Formulas (11)–(14), and the calculation results are shown in Figure 5. The classification of risk level is shown in Table 6.

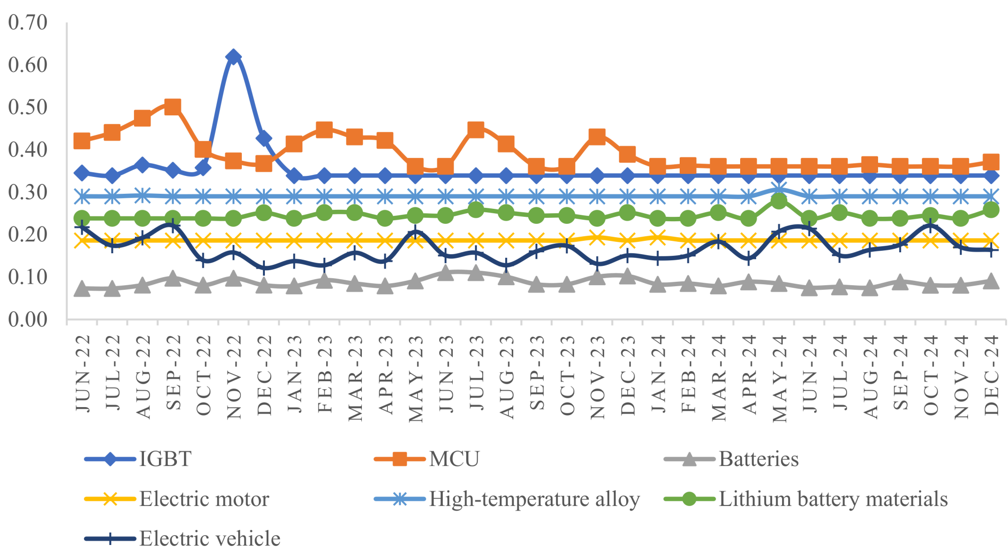

Figure 5. The dynamic risk value of each node in the new energy vehicle industrial chain.

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Table 6. The classification of risk level.

C_i^*	Risk Level
(0.7, 1]	Significant risk
(0.4, 0.7]	Greater risk
(0.3, 0.4]	Medium risk
(0.2, 0.3]	Slight risk
[0, 0.2]	No risk

Through the risk assessment of the seven nodes of the new energy vehicle industrial chain, it can be seen that IGBT and MCU are relatively fragile in the supply dimension and are affected by the impact of events in this dimension, resulting in fluctuations in the risk value. Among them, IGBT showed a high risk level at the end of 2022. MCU-related risks peaked at 0.5 in September 2022, remained around 0.4 throughout 2023, and virtually disappeared by 2024. Although the battery and lithium battery materials were impacted by risk events, the risk value did not fluctuate or fluctuated very little because the risk event did not occur in the fragile dimension. Electric motor and high-temperature alloy are not impacted by risk events, so the risk value reflects their static risk level. The competition and supply dimensions of high-temperature alloy are at a slight risk level and close to medium risk, which indicates that high-temperature alloy needs to be continuously paid attention to in future development to reduce the risk of its related dimensions. Risk levels for electric vehicles consistently remained within low-risk or risk-free. Despite numerous market events associated with the electric vehicle node, the market dimension does not constitute a fragile dimension for the electric vehicle node, thus manifesting no substantial risk.

3.3. Sensitivity Analysis

To assess the robustness of the dynamic risk index, a sensitivity analysis is conducted with respect to two key factors: the occurrence frequency of risk events and the indicator weights. The sensitivity to the indicator weights is examined first, followed by the sensitivity to event frequency.

The indicator weights determine the dimension static risks through the TOPSIS calculation. To assess the sensitivity of the static risk to the indicator weighting, each within-dimension indicator weight is perturbed by $+/-20\%$ and the dimension risks are recomputed using the TOPSIS procedure through a Monte Carlo simulation with one thousand random trials. As shown in Table 7, the static risk varies only within narrow ranges, and the fragile dimension is robust. Only the electric motor changes its fragile dimension in 1.3% of the trials, whereas the other six nodes retain their fragile dimension throughout. This indicates that the risk conclusions are stable with respect to indicator-weight uncertainty.

Table 7. The sensitivity of the static risk to indicator-weight perturbation.

Industrial Chain Node	Baseline Fragile Dimension	Fragile Dimension Changes Under $+/-20\%$	Static Risk Range
Lithium battery materials	Market	No (0%)	0.436–0.515
High-temperature alloy	Competitive	No (0%)	0.576–0.585
Electric motor	Market	Yes (1.3%, from market to competitive)	0.338–0.410
Batteries	Competitive	No (0%)	0.137–0.155
IGBT	Supply	No (0%)	0.661–0.699
MCU	Supply	No (0%)	0.718–0.724
Electric vehicle	Competitive	No (0%)	0.234–0.252

Building on these validated static risks, the sensitivity to event frequency is examined. Table 8 reports the critical event intensity e^* at which each node crosses each risk-level threshold in Table 6. The index is most sensitive to event frequency along the fragile dimension: MCU and IGBT, whose fragile dimension is supply, enter the greater-risk level at $e^* = 1.109$ and 1.180, respectively, and MCU reaches the significant-risk level at $e^* = 1.941$, whereas batteries and electric vehicles remain at no-risk or slight-risk levels even at event saturation ($e = 2$). This indicates that event-frequency surveillance should be prioritized on the high-vulnerability nodes.

Table 8. The critical event intensity e^* at which each node crosses each risk-level threshold.

Industrial Chain Node	Fragile Dimension	e^* (Reach Greater Risk)	e^* (Reach Significant Risk)	Dynamic Risk Value at $e = 2$
Lithium battery materials	Market	1.680	unreachable	0.476
High-temperature alloy	Competitive	1.379	unreachable	0.580
Electric motor	Market	unreachable	unreachable	0.372
Batteries	Competitive	unreachable	unreachable	0.146
IGBT	Supply	1.180	unreachable	0.678
MCU	Supply	1.109	1.941	0.721
Electric vehicle	Competitive	unreachable	unreachable	0.242

4. Discussion

4.1. Implications for Theory

The proposed DIMS advances industrial chain risk research in two theoretical directions. First, it bridges the long-standing divide between static vulnerability assessment and dynamic event monitoring by integrating them within a single, node-resolved framework, responding to the limitation that prior studies either assessed the chain as an aggregate whole or monitored events without linking them to specific vulnerable nodes. Second, it demonstrates that large language models such as DeepSeek can serve as semantic associators that surpass keyword-based methods, offering a transferable paradigm for coupling external textual signals with structured domain ontologies.

4.2. Implications for Practice and Policy

For practitioners and policymakers, the DIMS offers a near-real-time instrument to locate the fragile nodes of a given industrial chain and to track how external events elevate their risk. The empirical analysis shows that IGBT and MCU, the components with the highest static supply vulnerability, exhibited marked risk fluctuations when supply events occurred, whereas nodes whose fragile dimension was not hit remained stable. This indicates that policy attention and buffer-building, such as strategic reserves, diversified sourcing, and domestic substitution, should be prioritized for nodes that are both statically fragile and dynamically exposed. Because the industrial chain node can be redefined for any industrial chain, the system is reusable across sectors, supporting government industrial-chain security strategies and enterprise resilience planning.

4.3. Limitations of the Study and Future Research Directions

Several limitations should be acknowledged. First, the model is empirically tested only on the new energy vehicle industrial chain. Although the architecture is transferable, multi-chain validation is needed. Second, the indicator weights, the multiplicative fusion of static and dynamic hazards, the normalization ranges, and the risk-level thresholds were designed on the basis of domain logic and MCDM conventions rather than empirical or statistical optimization. An indicator-weight sensitivity analysis is reported in Section 3.2, confirming that the risk conclusions are robust to $+/-20\%$ weight perturbation. Broader scenario analyses are reserved for future work as the monitored event corpus expands. Third, deploying the system at scale involves data-acquisition pipelines, update latency, and false-news filtering, which are not fully addressed here. Future research will extend the indicator system, accumulate and re-label risk events to re-train the ERNIE models, conduct comparative and sensitivity experiments, and integrate rumor filtering.

5. Conclusions

Maintaining the stability of the industrial chain and preventing the risks of the industrial chain are key to maintaining the stable development of the economy. This paper constructs a DIMS to measure the risk level of the industrial chain from the perspective of each node of the industrial chain. The system is composed of an IC-SRAM and an IC-DEMM. The IC-SRAM uses the TOPSIS method to assess the static risk value of each node of the industrial chain from the three dimensions of competitive strength, supply dependence, and market dependence. The IC-DEMM uses a deep learning method to automatically identify the risk events of each node of the industrial chain and classifies them into the corresponding three dimensions. DeepSeek is used to associate events with industrial chain nodes. The dynamic industrial chain risk value is formed based on the results of static risk assessment and dynamic risk event monitoring. When the fragile dimension of the industrial chain node is impacted by risk events, it will show greater risks.

This paper takes the new energy vehicle industrial chain as an example, selects seven nodes in the new energy vehicle industrial chain, and collects the data from the second half of 2022 to 2024 for empirical analysis. IGBT, MCU, and electric vehicle have been impacted in their fragile dimensions by risk events, resulting in fluctuations in their risk values. For battery and lithium battery materials, because the risk event did not occur in the fragile dimension, the risk value did not fluctuate or fluctuated very little. Electric motor and high-temperature alloy are not impacted by risk events, and the risk value reflects their static risk level. The proposed DIMS can dynamically and effectively monitor the fluctuation of industrial chain risk. In the future, on the one hand, the evaluation of the static risk of the industrial chain can be further optimized, including the optimization and adjustment of dimensions and indicators. On the other hand, with the continuous accumulation and proofreading of risk events, the accuracy of identification and classification of industrial chain risk events can be further improved. The optimization of the two models can jointly improve the accuracy of monitoring the risk level of the industrial chain.

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References

1. Chauhan, C.; Akram, M.U.; Patky, J.; Chauhan, A. Mapping pathways for building resilient supply chains: A systematic literature review. *J. Clean. Prod.* **2023**, *425*, 138701. [CrossRef]
2. Hägele, S.; Grosse, E.H.; Ivanov, D. Supply chain resilience: A tertiary study. *Int. J. Integr. Supply Manag.* **2023**, *16*, 52–81. [CrossRef]
3. World Economic Forum. *The Global Risks Report 2026*; World Economic Forum: Geneva, Switzerland, 2026.
4. Shao, X.-F. Supply chain characteristics and disruption mitigation capability: An empirical investigation in China. *Int. J. Logist. Res. Appl.* **2013**, *16*, 277–295. [CrossRef]
5. Bode, C.; Macdonald, J.R. Stages of Supply Chain Disruption Response: Direct, Constraining, and Mediating Factors for Impact Mitigation. *Decis. Sci.* **2017**, *48*, 836–874. [CrossRef]
6. Parast, M.M. The impact of R&D investment on mitigating supply chain disruptions: Empirical evidence from U.S. firms. *Int. J. Prod. Econ.* **2020**, *227*, 107671. [CrossRef]
7. Cong, P.; Cao, J.; Yao, X.; Lin, Y.; Liu, H.; Ji, J.; Li, F. Risk Assessment of Earthquake Disaster Impact on Industrial Chain. *Technol. Earthq. Disaster Prev.* **2024**, *19*, 37–51.
8. OECD. *Export Restrictions on Industrial Raw Materials*; OECD: Paris, France, 2025.
9. Okabe, M.; Ohtani, H. Risk estimation for industrial safety in raw materials manufacturing. *J. Loss Prev. Process Ind.* **2009**, *22*, 176–181. [CrossRef]
10. Li, B.; Li, H.; Dong, Z.; Lu, Y.; Liu, N.; Hao, X. The global copper material trade network and risk evaluation: A industry chain perspective. *Resour. Policy* **2021**, *74*, 102275. [CrossRef]
11. Levner, E.; Ptuskin, A. Entropy-based model for the ripple effect: Managing environmental risks in supply chains. *Int. J. Prod. Res.* **2018**, *56*, 2539–2551. [CrossRef]
12. Wu, A.; Sun, Y.; Zhang, H.; Sun, L.; Wang, X.; Li, B. Research on Resilience Evaluation of Coal Industrial Chain and Supply Chain Based on Interval Type-2F-PT-TOPSIS. *Processes* **2023**, *11*, 566. [CrossRef]
13. Lin, J.; Li, X.; Luo, F.; Liu, W.; Tang, X.; Wang, M.; Li, Y. Security evaluation of China's indium industrial chain: Perspective on substance flow throughout the whole life cycle. *Sustain. Prod. Consum.* **2024**, *47*, 557–569. [CrossRef]
14. Hua, X.; Li, D.; Fu, Y.; Bi, K.; Ying, S.; Wang, R. Industrial chain risk assessment and early warning model combining hierarchical graph neural network and long short-term memory. *J. Comput. Appl.* **2024**, *44*, 3223–3231.
15. Huang, R.; Guo, S.; Zhou, Q.; Zhao, Y. Tail-risk contagion across key industrial chains of China. *Empir. Econ.* **2025**, *68*, 2119–2158. [CrossRef]
16. Hu, X.; Li, X.; Wang, C.; Yao, C.; Lim, M.K. Adaptive and risk recovery strategies for enhancing supply chain network resilience: A cascading failure perspective. *Ann. Oper. Res.* **2026**, 1–45. [CrossRef]
17. Tian, Y.; Choi, T.-M.; Ding, X.; Xing, R.; Zhao, J. A Grid Cumulative Probability Localization-Based Industrial Risk Monitoring System. *IEEE Trans. Autom. Sci. Eng.* **2019**, *16*, 557–569. [CrossRef]
18. Ganesh, A.D.; Kalpana, P. Supply chain risk identification: A real-time data-mining approach. *Ind. Manag. Data Syst.* **2022**, *122*, 1333–1354. [CrossRef]
19. Tang, H.; Yuan, Y.; Gong, T. Industrial Chain Disruption Events Monitoring with Deep Learning Methods: A Practical Application in China. *Int. J. Intell. Syst.* **2023**, *2023*, 3338184. [CrossRef]
20. Kim, Y. Convolutional Neural Networks for Sentence Classification. *arXiv* **2014**, arXiv:1408.5882.
21. Joulin, A.; Grave, E.; Bojanowski, P.; Mikolov, T. Bag of Tricks for Efficient Text Classification. *arXiv* **2016**, arXiv:1607.01759.
22. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv* **2018**, arXiv:1810.04805.
23. Sun, Y.; Wang, S.; Li, Y.; Feng, S.; Chen, X.; Zhang, H.; Tian, X.; Zhu, D.; Tian, H.; Wu, H. ERNIE: Enhanced Representation through Knowledge Integration. *arXiv* **2019**, arXiv:1904.09223.
24. Gao, Z.; Feng, A.; Song, X.; Wu, X. Target-Dependent Sentiment Classification with BERT. *IEEE Access* **2019**, *7*, 154290–154299. [CrossRef]
25. Jeong, C.; Jang, S.; Park, E.; Choi, S. A context-aware citation recommendation model with BERT and graph convolutional networks. *Scientometrics* **2020**, *124*, 1907–1922. [CrossRef]
26. Wang, T.; Lu, K.; Chow, K.P.; Zhu, Q. COVID-19 Sensing: Negative Sentiment Analysis on Social Media in China via BERT Model. *IEEE Access* **2020**, *8*, 138162–138169. [CrossRef]
27. Fan, Y.; Cao, X.; Xiao, H.; Zhou, W.; Jiang, W. Loan Question Answering Platform Based on ERNIE and Knowledge Graph. *Int. J. Softw. Sci. Comput. Intell.* **2022**, *14*, 1–16. [CrossRef]
28. Wang, C.; Feng, F. ERNIE based intelligent triage system. *J. Intell. Fuzzy Syst.* **2022**, *43*, 5013–5022. [CrossRef]
29. Gelastopoulos, G.; Keramydas, C. A systematic review of text mining analytics for supply chain risk management using online data. *Supply Chain Anal.* **2025**, *12*, 100167. [CrossRef]

30. Zogaan, W.A.; Ajabnoor, N.; Salamai, A.A. Leveraging deep learning for risk prediction and resilience in supply chains: Insights from critical industries. *J. Big Data* **2025**, *12*, 94. [CrossRef]
31. de la Cruz Madrigal, V.H.; Avelar Sosa, L.; Mejía-Muñoz, J.-M.; García Alcaraz, J.L.; Jiménez Macías, E. Dynamical System Modeling for Disruption in Supply Chain and Its Detection Using a Data-Driven Deep Learning-Based Architecture. *Logistics* **2025**, *9*, 51. [CrossRef]
32. AlMahri, S.; Xu, L.; Brintrup, A. Automating Supply Chain Disruption Monitoring via an Agentic AI Approach. *arXiv* **2026**, arXiv:2601.09680.
33. Xue, Z.; Wang, Y.; Huo, M. LLM-Grounded Explainable AI for Supply Chain Risk Early Warning via Temporal Graph Attention Networks. *arXiv* **2026**, arXiv:2603.04818.
34. Liu, A.; Feng, B.; Xue, B.; Wang, B.; Wu, B.; Lu, C.; Zhao, C.; Deng, C.; Zhang, C.; Ruan, C.; et al. DeepSeek-V3 Technical Report. *arXiv* **2024**, arXiv:2412.19437.
35. Behzadian, M.; Otaghsara, S.K.; Yazdani, M.; Ignatius, J. A state-of-the-art survey of TOPSIS applications. *Expert Syst. Appl.* **2012**, *39*, 13051–13069. [CrossRef]
36. Çelikbilek, Y.; Tüysüz, F. An in-depth review of theory of the TOPSIS method: An experimental analysis. *J. Manag. Anal.* **2020**, *7*, 281–300. [CrossRef]
37. Bertolini, M.; Esposito, G.; Romagnoli, G. A TOPSIS-based approach for the best match between manufacturing technologies and product specifications. *Expert Syst. Appl.* **2020**, *159*, 113610. [CrossRef]
38. Ervural, B.C.; Zaim, S.; Demirel, O.F.; Aydin, Z.; Delen, D. An ANP and fuzzy TOPSIS-based SWOT analysis for Turkey's energy planning. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1538–1550. [CrossRef]
39. Hu, Y.; Wu, L.; Shi, C.; Wang, Y.; Zhu, F. Research on optimal decision-making of cloud manufacturing service provider based on grey correlation analysis and TOPSIS. *Int. J. Prod. Res.* **2020**, *58*, 748–757. [CrossRef]
40. Tang, H.; Shi, Y.; Dong, P. Public blockchain evaluation using entropy and TOPSIS. *Expert Syst. Appl.* **2019**, *117*, 204–210. [CrossRef]
41. Yang, L.; Li, Y. A new method for ranking the usefulness of negative online reviews based on combined weighting method and improved TOPSIS. *J. Intell. Fuzzy Syst.* **2022**, *42*, 3719–3736. [CrossRef]
42. Mao, N.; Song, M.; Deng, S. Application of TOPSIS method in evaluating the effects of supply vane angle of a task/ambient air conditioning system on energy utilization and thermal comfort. *Appl. Energy* **2016**, *180*, 536–545. [CrossRef]
43. Ding, X.; Chong, X.; Bao, Z.; Xue, Y.; Zhang, S. Fuzzy Comprehensive Assessment Method Based on the Entropy Weight Method and Its Application in the Water Environmental Safety Evaluation of the Heshangshan Drinking Water Source Area, Three Gorges Reservoir Area, China. *Water* **2017**, *9*, 329. [CrossRef]
44. Hwang, C.-L.; Yoon, K. *Multiple Attribute Decision Making: Methods and Applications*; Springer: Berlin/Heidelberg, Germany, 1981.