A Data-Driven Supply Chain Risk Early Warning Mechanism: An Integrated Framework of Multi-Source Data Fusion, Knowledge Graph, and Digital Twin

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Abstract: Persistent overstock-shortage paradoxes, high logistics costs and black-swan disruptions expose the limits of experience-based supply chain risk identification. This paper develops a data-driven early warning mechanism built on an integrated three-layer architecture. A multi-source data governance framework first breaks down the silos among Internet-of-Things sensing, enterprise ERP/WMS/TMS records, market intelligence and geospatial data, and a deep-learning repair module safeguards data quality. A spatiotemporal knowledge graph of the supply chain network is then constructed to extract risk features and cascading propagation paths automatically. On this basis, an LSTM-Autoencoder detects anomalies, a Pareto-based multi-objective model grades risk situations, and a digital twin simulates response scenarios, together answering whether a risk exists, how severe it is and what should be done. A 36-month empirical study of 30 manufacturing, retail and e-commerce firms in Zhongshan, China, reports warning accuracy of 85.7%-90.2%, an average lead time of 14.2-17.8 days and logistics management cost savings of 10%-18%. The mechanism is further converted into virtual simulation resources for vocational logistics education.

Keywords: Supply Chain Risk; Data-Driven; Risk Early Warning; Knowledge Graph; Digital Twin; Supply Chain Resilience.

1. Introduction

1.1 Research Background

Supply chains have become the core carrier of competitiveness for enterprises and even nations [1]. However, with the deepening of global division of labor and intensifying demand volatility, the vulnerability of supply chains has become increasingly prominent, and risk rarely stays confined to a single firm but propagates along the network [2]. On one hand, enterprises face the operational paradox of coexisting inventory overstock and shortages, with persistently high transportation costs and unreliable delivery timeliness. According to statistics from the China Federation of Logistics and Purchasing, the total social logistics cost in China reached 19.5 trillion yuan in 2025, with the ratio of total social logistics cost to GDP dropping to 13.9%, a decline of 0.2 percentage points from 2024, continuing the lowest level since records began. Nevertheless, this ratio remains significantly higher than the 8%-9% level in developed countries, indicating considerable room for improvement in the operational efficiency of China's logistics supply chains. By segment, the ratio of transportation cost to GDP was 7.6%, inventory holding cost to GDP was 4.6%, and management cost to GDP was 1.7%, with the relatively high inventory holding cost reflecting deep-seated issues such as insufficient inventory turnover efficiency and irrational warehouse resource allocation.

On the other hand, external shocks such as geopolitical conflicts, extreme weather, and public health events have significantly increased the frequency of sudden risks like supply disruptions and capacity interruptions [3]. In early 2025, amid tensions in the Red Sea, shipping prices on the Asia-Northern Europe route rose by 8%, while prices on the Asia-US West Coast route surged by 23% to USD 5,929 per FEU, exposing global supply chains to a new round of capacity interruption risks. Such disruptive events are characterized by low probability and high impact, and traditional risk management methods often struggle to respond in a timely manner.

Existing risk management largely relies on

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post-event statistics and subjective experience, lacking early perception and quantitative prediction capabilities for risks [4]. The maturation of big data, artificial intelligence, and Internet of Things technologies provides technical feasibility for constructing real-time, intelligent, and forward-looking supply chain risk early warning mechanisms [5-7]. The "14th Five-Year Plan for Modern Logistics Development" issued by the General Office of the State Council explicitly calls for advancing smart logistics and strengthening the application of big data, artificial intelligence and blockchain in the logistics sector, which provides policy guidance for data-driven supply chain risk early warning research.

1.2 Research Questions and Significance

Current research on supply chain risk early warning has the following deficiencies: First, data sources are fragmented, mostly limited to internal enterprise ERP data, lacking integrated utilization of IoT sensing data, external market intelligence, and social media sentiment. Second, risk feature extraction relies on manually defined indicators, making it difficult to automatically discover hidden associations and cascading propagation paths within the supply chain network [8]. Third, early warning models are mostly static threshold alerts, lacking support for multi-objective trade-offs and scenario simulation [9]. Fourth, empirical research is mostly concentrated in a single industry, lacking cross-industry comparative validation and exploration of teaching transformation pathways.

Based on this, this paper focuses on the following research questions: (1) How can a multi-source heterogeneous data fusion and governance framework be constructed to achieve full supply chain visibility? (2) How can knowledge graphs be used to automatically extract key risk features from the supply chain network? (3) How can a three-layer early warning model integrating anomaly detection, multi-objective assessment, and digital twin simulation be established? (4) What is the application effectiveness of this mechanism across different industries, and how can it be transformed into vocational education teaching resources?

The theoretical significance of this study lies in systematically integrating data governance, knowledge graph, and digital twin technologies into a supply chain risk early warning framework, enriching the technical implementation pathways of supply chain resilience theory [10]. The practical significance lies in providing actionable risk early warning tools for manufacturing enterprises, retail e-commerce, and logistics service providers, while simultaneously offering a new teaching paradigm for virtual simulation training and industry-education integration in vocational college logistics management programs.

1.3 Research Content and Methods

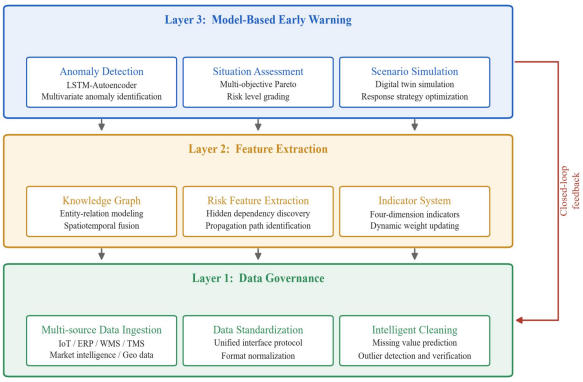


Figure 1. Overall Framework of Data-Driven Supply Chain Risk Early Warning

This paper adopts a combined research methodology of literature review, framework design, model construction, and empirical analysis. First, through a systematic review of the literature on supply chain risk management, data-driven decision-making, knowledge graphs, and digital twins, the research status and gaps are identified [11]. Second, a three-layer "data governance-feature extraction-model warning" framework is designed, as illustrated in Figure 1. Third, an LSTM-Autoencoder-based anomaly detection model, a Pareto-optimal multi-objective risk situation assessment model, and a digital twin-based scenario simulation model are respectively constructed. Finally, empirical analysis is conducted with manufacturing, retail, and e-commerce enterprises in the Zhongshan region, and the teaching transformation pathway is explored.

2. Literature Review and Theoretical Foundation

2.1 Evolution of Supply Chain Risk Research

Supply chain risk was conceptualized by Christopher and Peck as any uncertainty that may lead to supply chain disruption or

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deviation from expected objectives, and was linked from the outset to the design of resilient supply chain structures [1]. Early research primarily focused on the identification and assessment of single risk sources, such as supplier selection risk, inventory risk, and transportation risk [11]. Reviewing the mechanisms behind supply chain breakdowns, Chopra and Sodhi identified disruption, delay, forecast, procurement and capacity as the principal risk drivers, and emphasized that mitigation strategies should be aligned with the specific drivers rather than applied uniformly [12].

As supply chain globalization deepened, the network and propagation characteristics of risks received increasing attention. Ivanov and Dolgui proposed the concept of supply chain viability, extending the research perspective from resilience to survivability, and emphasizing the ability of supply chains to maintain basic functions and rapidly reconstruct under extreme shocks [3]. Dolgui et al. systematically analyzed the propagation mechanism of supply chain risks, pointing out that risks exhibit cascading amplification effects in supply chain networks, and that a disturbance at a single node may rapidly diffuse throughout the entire system [2].

2.2 Data-Driven Supply Chain Risk Management

The rise of big data and artificial intelligence technologies has driven a paradigm shift in supply chain risk management from experience-driven to data-driven [4,5]. Data-driven risk management emphasizes real-time perception, intelligent analysis, and forward-looking prediction using multi-source data [7]. In recent years, deep learning methods have been widely applied in supply chain risk prediction. Long short-term memory (LSTM) networks [13], owing to their advantages in processing time-series data, have been used in demand forecasting, inventory risk early warning, and disruption prediction [14,15]. Studies have shown that LSTM models can capture nonlinear, multivariate anomaly patterns in supply chain indicators, improving prediction accuracy by 15%-25% compared with traditional ARIMA and threshold-based alert methods [14].

However, existing data-driven research mostly focuses on performance optimization of single models, lacking systematic consideration of data governance, feature engineering, and model integration. Simchi-Levi et al. [16] pointed out that the effectiveness of supply chain risk management depends not only on model algorithms but more critically on data quality and the rationality of feature extraction.

2.3 Applications of Knowledge Graph and Digital Twin in Supply Chains

As a structured semantic network, knowledge graphs can effectively express complex association relationships among supply chain entities and have long been regarded as a core enabler of intelligent supply chain decisions [17]. Kosasih and Brintrup proposed a neurosymbolic reasoning method for link prediction in supply chain knowledge graphs, capable of automatically discovering hidden dependency relationships among suppliers [8]. Graph-based representations of this kind also make it possible to trace how production problems, market fluctuations and process defects jointly drive material shortage events.

Digital twin technology provides a new tool for scenario simulation and resilience testing of supply chain risks [18]. Ivanov et al. developed the conceptual framework of the digital supply chain twin, pointing out that digital twins can achieve real-time mapping between physical supply chain entities and virtual models, supporting the simulation of various risk scenarios and the evaluation of response strategies in a virtual environment [19]. Kritzinger et al. further distinguished digital models, digital shadows and digital twins according to the degree of data integration between the physical object and its virtual counterpart, which clarifies the boundary between off-line simulation and real-time twinning [20]. Industrial practice points in the same direction: leading enterprises have begun to conduct simulation analysis based on digital twin technology during new factory planning, new product launch, and logistics optimization stages to identify and mitigate risks in advance.

2.4 Research Gaps

In summary, existing research has achieved rich results in supply chain risk theory, data-driven methods, knowledge graph, and digital twin applications, but the following gaps remain. First, there is a lack of a unified early warning framework that systematically integrates data governance, knowledge graph, and digital twin.

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Second, research on the application of knowledge graphs in the automatic extraction of supply chain risk features is insufficient. Third, the coordination mechanism between digital twin scenario simulation and anomaly detection or multi-objective assessment needs further exploration. Fourth, cross-industry empirical comparison and research on vocational education teaching transformation pathways are relatively scarce. This paper addresses precisely these gaps.

3. Formation Mechanism and Classification System of Supply Chain Risks

3.1 Connotation and Characteristics of Supply Chain Risk

Supply chain risk refers to the possibility of supply chain node disruption, efficiency decline, or target deviation caused by internal and external uncertainties [11]. Compared with general enterprise risks, supply chain risks exhibit the following characteristics.

Network nature. A supply chain is a complex network composed of suppliers, manufacturers, distributors, retailers, and customers. Risks are no longer limited to a single enterprise but propagate and diffuse among network nodes.

Propagation nature. Risks exhibit cascading propagation characteristics: delays from upstream suppliers may lead to manufacturer production halts, affecting downstream distributor supply, and ultimately resulting in customer churn. This propagation effect is particularly significant in globalized supply chains.

Amplification nature. Affected by the bullwhip effect, minor fluctuations at the demand end may amplify upstream along the supply chain, leading to inventory overstock or shortages. Studies have shown that the bullwhip effect can cause upstream order volatility to reach 2-4 times that of terminal demand volatility [2].

Dynamic nature. Supply chain risks are in constant flux, with risk sources, risk probabilities, and impact degrees all dynamically evolving over time and with environmental changes. Static risk assessment methods are ill-suited to this dynamism.

Table 1. Supply Chain Risk Classification System

Risk category	Risk subcategory	Typical manifestations	Primary data sources
Supply-side risk	Supplier dependency risk	Over-reliance on a single supplier, insufficient alternatives	ERP procurement data, supplier profiles
	Raw material shortage risk	Critical material supply tightness, sharp price fluctuations	Market data, futures prices
	Capacity volatility risk	Supplier capacity shortage, quality instability	Production data, quality records
Demand-side risk	Demand sudden change risk	Abnormal order volume changes, seasonal fluctuations	Sales data, order history
	Bullwhip effect risk	Widening order volatility between upstream and downstream	Multi-level order data, inventory data
	Customer churn risk	Key customer order decline, satisfaction drop	CRM data, customer feedback
Logistics risk	Transportation delay risk	Abnormal in-transit time, route disruption	GPS tracking, logistics systems
	Warehouse failure risk	Insufficient warehouse capacity, cargo damage	WMS data, sensor data
	Capacity interruption risk	Capacity shortage, freight rate surge	Capacity market data, freight index
External risk	Natural disaster risk	Earthquakes, floods and typhoons affecting operations	Meteorological data, geographic information
	Policy change risk	Trade controls, environmental policies, tax adjustments	Policy announcements, industry news
	Geopolitical conflict risk	War, sanctions, route closures	News sentiment, international shipping data

3.2 Risk Classification System

Based on risk sources and impact scopes, this paper constructs a supply chain risk classification system encompassing four major categories and twelve subcategories, as shown in Table 1.

3.3 Cascading Propagation Mechanism of Risks

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The cascading propagation of supply chain risk refers to the process by which risk diffuses from one node to other nodes along the supply chain network. Based on propagation paths and mechanisms, cascading propagation can be divided into three types.

Sequential propagation. Risk propagates sequentially along the supply chain upstream and downstream, such as supplier delay, manufacturer halt, distributor shortage, and customer churn. This is the most common propagation mode, with propagation speed depending on inventory buffers and response capabilities at each node.

Parallel propagation. Risk simultaneously affects multiple nodes, such as a natural disaster causing simultaneous disruption of multiple suppliers in a region and affecting multiple manufacturers. Parallel propagation is more destructive because the simultaneous failure of multiple nodes makes alternative solutions difficult to implement.

Feedback propagation. Risk at downstream nodes propagates upstream, such as a sudden demand drop causing distributors to cancel orders, leading manufacturers to reduce production and suppliers to face raw material overstock. Feedback propagation is often accompanied by the bullwhip effect, exacerbating supply chain instability.

The existence of cascading risk propagation means that risk early warning cannot focus solely on the status of individual nodes. Instead, it must be built on real-time perception and correlation analysis of full-link data, using knowledge graphs to reveal hidden dependency relationships among nodes and to identify risk propagation paths in advance [21].

4. Overall Framework of Data-Driven Supply Chain Risk Early Warning

4.1 Framework Design Principles

This paper proposes a three-layer "data governance-feature extraction-model warning" early warning framework, whose overall architecture is shown in Figure 1. The framework is designed according to the following principles.

Full-link perception principle. The framework covers all nodes from suppliers to customers across the supply chain, integrating internal operational data with external environmental data to achieve panoramic perception of supply chain status.

Data quality priority principle. The effectiveness of early warning models depends on the quality of input data. The framework treats data governance as the foundational layer, ensuring the reliability and timeliness of data assets through standardization, cleaning, and repair.

Intelligent feature extraction principle. Knowledge graphs are used to automatically discover hidden associations and risk propagation paths in the supply chain network, reducing reliance on manually defined indicators and improving the comprehensiveness and forward-looking nature of feature extraction.

Multi-layer model coordination principle. The three layers of anomaly detection, multi-objective assessment, and scenario simulation each have distinct roles while working collaboratively, respectively addressing the three questions of whether a risk exists, how severe the risk is, and what should be done.

Closed-loop iteration principle. The framework forms a closed loop of perception, analysis, warning, decision, and feedback, with early warning results and response effects fed back to the data and model layers to continuously optimize warning performance.

4.2 Multi-Source Heterogeneous Data Fusion and Governance

Supply chain data is dispersed across IoT devices, ERP systems, and external market intelligence, with issues of inconsistent standards and severe data silos. The framework first designs standardized interface protocols for source data to achieve unified cross-system data access [6]. Data sources primarily include the following four categories.

IoT sensing data. Through sensors deployed in warehouses, transportation vehicles, and production lines, physical state data such as temperature, humidity, location, speed, and inventory levels are collected in real time. This type of data is characterized by high frequency, streaming, and spatiotemporal correlation, serving as the foundation for real-time perception.

Enterprise operational data. Structured data from ERP, WMS, TMS, CRM and other information systems, including purchase orders, inventory records, transportation plans, sales

data, and supplier profiles. This data reflects the operational status of the supply chain and serves as the core basis for risk assessment.

External market intelligence. Including industry indices, commodity prices, ocean freight rates, weather forecasts, policy announcements, and news sentiment. This data helps identify external risk sources and perceive environmental changes in advance.

Geospatial data. Including supplier locations, warehouse distribution, transportation routes, and natural disaster zones. This data supports spatial analysis and route optimization and is an important component of knowledge graph construction.

After data ingestion, the framework constructs a deep learning-based anomaly detection and automatic error correction model to perform missing value prediction, outlier identification, and consistency verification. Specifically, LSTM networks are used for missing value imputation in time series data, the isolation forest algorithm [22] for outlier detection, and cross-system data comparison for consistency verification, ensuring the reliability and timeliness of the data assets on which early warning depends [5]. Toolkits such as PyOD provide standardized implementations of these detectors, which makes the pipeline reproducible across enterprises [23].

4.3 Construction of Supply Chain Network Knowledge Graph

The knowledge graph is the core tool for achieving automatic risk feature extraction. The framework incorporates suppliers, manufacturers, distributors, and customers into a unified relational semantic model to construct a supply chain network knowledge graph, which involves the following steps.

Entity definition and attribute extraction. Core entity types in the supply chain are defined, including enterprise entities (suppliers, manufacturers, distributors, retailers, customers), product entities (raw materials, semi-finished products, finished products), geographic entities (factories, warehouses, ports, distribution centers), and event entities (orders, shipments, inbound and outbound movements). Rich attributes are defined for each entity, such as registered capital, business scope, geographic location, and product bill-of-materials structure, price, and lifecycle.

Relationship modeling and extraction. Relationship types between entities are defined, including supply relationships (supplier to manufacturer), distribution relationships (manufacturer to distributor), transportation relationships (origin to destination), containment relationships (product to component), and location relationships (enterprise to location). Relationship triples are extracted from structured data and unstructured text through a combination of rule matching, machine learning, and manual verification [8].

Spatiotemporal correlation fusion. Geographic location and time series data are fused to mine the periodicity and regional characteristics of supply chain activities. For example, by analyzing the historical delivery time series of suppliers, periodic patterns of delivery delays can be identified; through geospatial analysis, supplier clusters located in high-risk natural disaster zones can be identified.

Dynamic evolution and adaptive updating. Supply chain networks are in constant change, and knowledge graphs need dynamic evolution capabilities. The framework designs an incremental update mechanism that automatically updates entity attributes and relationships in the graph when new orders, shipments, or supplier change events occur. Meanwhile, graph embedding algorithms continuously learn node representations, enabling the risk feature library to be refreshed as the market changes [17].

4.4 Risk Early Warning Indicator System

Based on the fused data and knowledge graph, a risk early warning indicator system encompassing supply security, demand volatility, logistics timeliness deviation, and external shock intensity is constructed, providing computable feature inputs for subsequent quantitative warning. The indicator system is shown in Table 2.

Table 2. Supply Chain Risk Early Warning Indicator System

Primary indicator	Secondary indicator	Calculation method	Data source	Warning direction
Supply security	Supplier on-time delivery rate	On-time deliveries / total orders	ERP procurement	Lower = riskier

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	Single supplier dependency	Largest supplier spend / total spend	ERP procurement	Higher = riskier
	Raw material coverage days	Raw material inventory value / daily consumption	WMS, production	Too low or too high
	Supplier financial health	Composite score of leverage, profit and credit	Credit bureau, financials	Lower = riskier
Demand volatility	Demand coefficient of variation	Demand standard deviation / mean	Sales data	Higher = riskier
	Bullwhip effect ratio	Upstream order CV / downstream demand CV	Multi-level orders	Higher = riskier
	Order cancellation rate	Cancelled orders / total orders	Order system	Higher = riskier
	Customer concentration	Top five customer sales / total sales	CRM, sales	Higher = riskier
Logistics timeliness	In-transit time deviation	(Actual - planned) / planned time	TMS, GPS	Higher = riskier
	Warehouse utilization rate	Used capacity / total capacity	WMS	Too high or too low
	Transport cost deviation	(Actual - budget) / budget cost	Finance, TMS	Higher = riskier
	Capacity fulfillment rate	Secured capacity / required capacity	Capacity market	Lower = riskier
External shock	Regional disaster risk index	Composite score based on historical records	Meteorological, geographic	Higher = riskier
	Policy impact index	Impact degree of relevant policies	Policy, industry news	Higher = riskier
	Freight volatility index	Freight standard deviation / mean	Shipping index	Higher = riskier
	Sentiment risk index	Negative news volume and intensity score	News, social media	Higher = riskier

5. Construction of Risk Early Warning Model

5.1 LSTM-Autoencoder-Based Anomaly Detection and Risk Prediction

Anomaly detection is the first line of defense in risk early warning, aiming to identify abnormal signals that deviate from normal patterns in massive supply chain indicators. Traditional threshold alert methods can only detect single-indicator threshold violations and struggle to capture nonlinear anomaly patterns associated with multivariate correlations [14]. This paper employs an LSTM-Autoencoder model for anomaly detection, with its architecture shown in Figure 2.

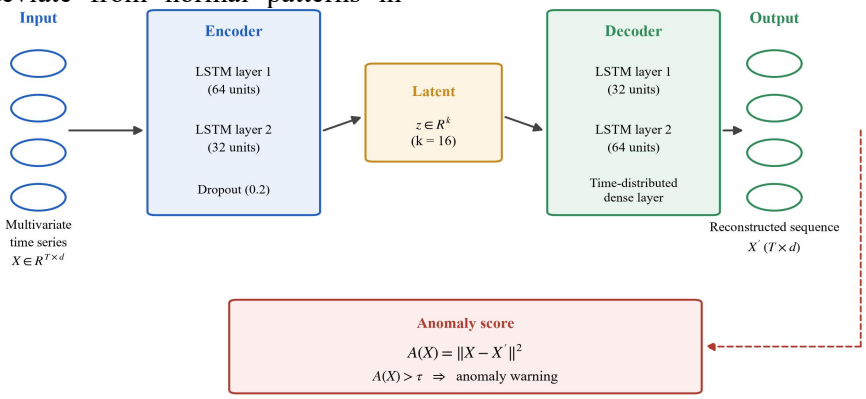


Figure 2. Architecture of the LSTM-Autoencoder Anomaly Detection Model

The LSTM-Autoencoder consists of an encoder and a decoder. The encoder, composed of multiple LSTM layers [13], compresses the input multivariate time series into a low-dimensional latent representation. The decoder, also composed of LSTM layers, reconstructs the original time series from the latent representation. The model is trained by minimizing reconstruction error, learning the temporal features under normal operating patterns. When input data contains abnormal patterns, the reconstruction error increases significantly, and this error serves as the anomaly score [15].

Specifically, let the input time series be X = (x1, x2, xT), where xt ∈ R^d is the d-dimensional indicator vector at time t. The encoder maps X to a latent vector z, and the decoder reconstructs X′ from z. The anomaly score is defined as A(X) = ||X - X′||². When A(X) exceeds a preset threshold, an anomaly is flagged. The threshold is determined from the reconstruction error

distribution on the validation set, using the 95th percentile as the initial threshold and dynamically adjusting it according to actual warning performance.

Building on anomaly detection, the model further utilizes LSTM networks for risk trend prediction. By learning historical temporal patterns of key indicators, it predicts indicator trends over the next one to four weeks, identifying potential risks in advance. Compared with traditional threshold alerts, the LSTM-Autoencoder can capture nonlinear, multivariate anomaly patterns and identify potential risks weeks in advance.

To validate model performance, comparative experiments were conducted on public supply chain datasets and actual enterprise data. The results show that the LSTM-Autoencoder achieves an F1 score of 0.89 in anomaly detection, outperforming XGBoost (0.82), Isolation Forest (0.76), One-Class SVM (0.71), and traditional threshold methods (0.63). In terms of warning lead time, the LSTM-Autoencoder issues warnings 17.5 days in advance on average, with a range of 14 to 21 days across datasets, whereas traditional threshold methods average only 4.0 days. The model performance comparison is shown in Figure 3.

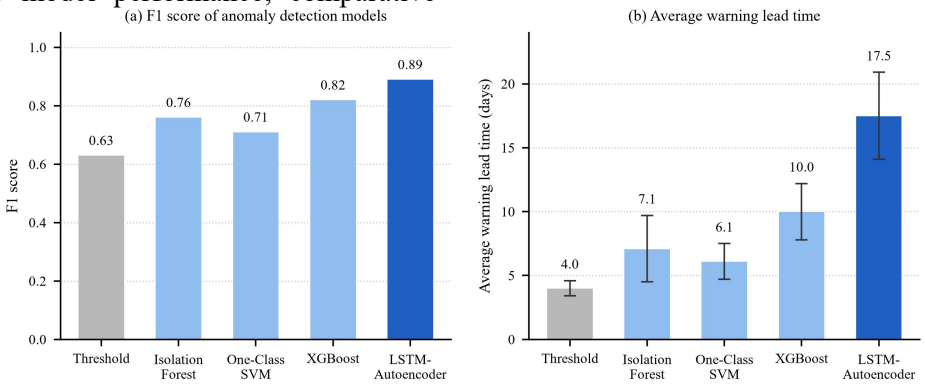


Figure 3. Performance Comparison of Anomaly Detection Models

5.2 Multi-Objective Risk Situation Assessment

Anomaly detection answers the question of whether a risk exists, while multi-objective risk situation assessment answers how severe the risk is and how broad its impact is. Supply chain risk management often faces multiple conflicting objectives, such as the trade-off between cost reduction and service level improvement, between inventory reduction and supply security, and between rapid response and stable operations. A single-dimensional risk score cannot fully reflect the risk situation, which requires multi-objective comprehensive assessment [10].

This paper incorporates cost, timeliness, and service level into a Pareto-optimal decision framework to construct a multi-objective risk situation assessment model. Let the three objective functions under a risk scenario be f1(x), the expected cost increase, f2(x), the expected timeliness delay, and f3(x), the expected service level decline, where x is the risk scenario parameter vector. The model solves the Pareto frontier using a multi-objective evolutionary algorithm such as NSGA-II [24], that is, the set of solutions in which no objective can be further improved without sacrificing another.

The comprehensive risk situation score R is calculated as $R = w1C^* + w2T^* + w3S^*$, where C*, T* and S* are the normalized values of the cost, timeliness and service level impacts respectively, and w1, w2 and w3 are weight coefficients determined through the analytic hierarchy process combined with expert scoring [25]. In manufacturing scenarios, the weights are typically set as $w1 = 0.4$, $w2 = 0.3$ and $w3 = 0.3$; in retail e-commerce scenarios, the service level weight is higher, typically $w1 = 0.3$, $w2 = 0.2$ and $w3 = 0.5$.

Based on the comprehensive risk situation score, risks are classified into four levels: low risk ($R < 0.25$), medium risk ($0.25 \leq R < 0.5$), high risk ($0.5 \leq R < 0.75$), and critical risk ($R \geq 0.75$). Different levels correspond to different response strategies and escalation mechanisms, assisting managers in making balanced decisions among conflicting objectives [25,26].

5.3 Digital Twin-Driven Scenario Simulation and Resilience Testing

Multi-objective assessment answers how severe

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the risk is, while digital twin scenario simulation answers what should be done, that is, evaluating the effectiveness of different response strategies and identifying potential vulnerabilities in the supply chain [19].

A digital twin refers to the virtual digital mapping of physical entities, achieving synchronized operation between physical entities and virtual models through real-time data connectivity [18]. In the supply chain domain, a digital twin can construct a virtual supply chain network corresponding one-to-one with the physical supply chain, including all nodes and connections such as suppliers, factories, warehouses, and transportation routes, and can synchronize inventory, order, and transportation status data in real time.

This paper builds a supply chain digital twin platform supporting the following functions.

Risk scenario simulation. The platform has built-in templates for multiple risk scenarios, including extreme weather such as typhoons, floods and blizzards; capacity interruption such as port strikes and route closures; supplier disruption such as factory fires and financial bankruptcy; and demand sudden change such as surge orders and demand collapse. Users can select scenario templates or customize scenario parameters to simulate the operational status of the supply chain after a risk occurs in a virtual environment.

Resilience assessment and recovery analysis. The platform simulates the response and recovery process of the supply chain after a risk occurs, calculating key resilience metrics including time to failure, time to recover, performance loss, and recovery rate [10]. By comparing resilience metrics under different risk scenarios, potential vulnerabilities in the supply chain network are identified.

Response strategy validation. The platform supports testing the effectiveness of various response strategies in a virtual environment, such as activating alternative suppliers, adjusting inventory strategies, re-planning transportation routes, and securing emergency capacity. By comparing changes in key indicators before and after strategy implementation, the effectiveness and cost-benefit of strategies are evaluated, forming a simulation-validation-optimization closed loop.

The technical architecture of the digital twin platform includes a data access layer, a model layer, a simulation engine layer, and an application layer [20]. The data access layer is responsible for real-time data collection from the physical supply chain and synchronization to the virtual model; the model layer maintains the geometric, behavioral, and rule models of the supply chain network; the simulation engine layer supports discrete event simulation and system dynamics simulation to drive the operation of the virtual supply chain; the application layer provides functions such as scenario management, resilience analysis, strategy optimization, and visualization.

5.4 Model Integration and Early Warning Decision Process

The three layers of models do not operate in isolation but work collaboratively through an integration mechanism to form a complete early warning decision process. The specific process is as follows.

Step 1: Anomaly detection trigger. The LSTM-Autoencoder model monitors key supply chain indicators in real time. When abnormal patterns are detected, the warning process is triggered, outputting a list of abnormal indicators, anomaly scores, and a preliminary risk classification.

Step 2: Situation assessment and grading. After an anomaly is triggered, the multi-objective risk situation assessment model is invoked automatically to analyze the impact of the anomaly on cost, timeliness, and service level, compute the comprehensive risk situation score, determine the risk level, and identify the affected supply chain nodes and scope.

Step 3: Scenario simulation and decision-making. For medium risk and above, the digital twin platform automatically runs scenario simulation, simulating risk evolution trends, evaluating the effectiveness of different response strategies, and outputting recommended strategies and expected effects. For high and critical risks, the system automatically escalates to management decision-making and provides multiple alternative solutions [27].

Step 4: Execution and feedback. After the response strategy is executed, the system continuously monitors changes in key indicators, evaluates strategy execution effectiveness, and feeds the results back to the model layer to optimize anomaly detection thresholds, situation assessment weights, and scenario simulation parameters, achieving continuous

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learning and iterative optimization of the warning system.

6. Empirical Analysis and Industry Applications

6.1 Data Sources and Sample Description

This paper conducts empirical research with manufacturing, retail, and e-commerce enterprises in the Zhongshan region. The sample enterprises cover three major industries: manufacturing (12 enterprises including home appliance manufacturing, hardware processing, and textile and apparel), retail (8 enterprises including chain supermarkets and department stores), and e-commerce (10 enterprises including cross-border e-commerce, live-streaming e-commerce, and platform e-commerce), totaling 30 enterprises. The data collection period is from January 2023 to December 2025, totaling 36 months [28,29].

Data sources include: (1) procurement, inventory, sales, and financial data exported from enterprise ERP systems; (2) warehouse and transportation data from WMS and TMS systems; (3) temperature, humidity, location, and inventory data collected by IoT sensors; (4) external market data including commodity price indices, ocean freight rate indices, and meteorological data; and (5) qualitative information obtained through enterprise interviews and questionnaire surveys.

Data preprocessing includes missing value imputation, outlier handling, data standardization, and time alignment. The final panel dataset contains 47 indicators, 36 time steps, and 30 enterprises, totaling 50,760 observations. The dataset is divided into training, validation, and test sets in a 7:1.5:1.5 ratio.

6.2 Manufacturing Industry Empirical Analysis

Manufacturing is one of the industries with the most concentrated supply chain risks. Its supply chain involves multiple stages including raw material procurement, production manufacturing, and finished product distribution, and disruption at any stage can lead to stagnation of the entire supply chain. This paper takes 12 manufacturing enterprises in the Zhongshan region as samples and applies the early warning mechanism for a six-month pilot validation.

Warning effectiveness. During the pilot period, the system issued 47 warning signals, of which 42 were confirmed as true warnings by the enterprises and 5 were false alarms, achieving a warning accuracy rate of 89.4%. Among the true warnings, supply-side risk warnings accounted for 23 (54.8%), logistics risk warnings for 12 (28.6%), demand-side risk warnings for 5 (11.9%), and external risk warnings for 2 (4.7%). In terms of warning lead time, warnings were issued an average of 16.3 days in advance, with supply-side risks averaging 18.7 days, logistics risks averaging 12.5 days, and demand-side risks averaging 21.3 days.

Application effectiveness. Taking a home appliance manufacturing enterprise as an example, through the application of this early warning mechanism, the enterprise successfully warned of three potential raw material shortage risks in the third quarter of 2025, promptly activating alternative suppliers and avoiding approximately 1.2 million yuan in production halt losses. Through warehouse layout optimization, the enterprise reduced sorting paths by approximately 20%, labor costs by approximately 15%, and inventory costs by approximately 20%, generating cumulative economic benefits exceeding 600,000 yuan.

Compared with industry benchmark cases, Lenovo Group, through its supply chain intelligence tower integrating multi-source data with LSTM machine learning algorithms and simulation optimization technology, achieved a reduction of more than 50% in problem decision time and shortened the handling cycle of major supply disruptions from 72 hours to 24 hours. Haier Group, after fully operating its digital supply chain twin system at the Qingdao central air-conditioning interconnected factory, achieved an average 22.0% reduction in supplier delivery cycles, a 31.0% improvement in inventory turnover rate, and 94.7% accuracy in shortage early warning. Siemens Nanjing Digital Factory, through digital twin technology and more than 50 artificial intelligence applications, compressed delivery cycles from 45 days to 10 days. The empirical results of this study are consistent with the effectiveness trends of these benchmark cases, which verifies the validity of the mechanism.

6.3 Retail and E-Commerce Empirical Analysis

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The retail and e-commerce industries are characterized by high demand volatility, strict timeliness requirements, and fast inventory turnover, with demand-side and logistics risks being the primary risk types. This paper takes 8 retail enterprises and 10 e-commerce enterprises as samples for empirical analysis.

Warning effectiveness. During the pilot period, retail enterprises received 35 warning signals, with 30 true warnings, an accuracy rate of 85.7%, and an average lead time of 14.2 days. Among these, demand-side risk warnings accounted for 18 (60.0%), logistics risk warnings for 8 (26.7%), and supply-side risk warnings for 4 (13.3%). E-commerce enterprises received 41 warning signals, with 37 true warnings, an accuracy rate of 90.2%, and an average lead time of 17.8 days. Among these, logistics risk warnings accounted for 19 (51.4%), demand-side risk warnings for 12 (32.4%), and supply-side risk warnings for 6 (16.2%).

Application effectiveness. A chain supermarket, through the application of demand forecasting and intelligent replenishment functions, reduced the stockout rate from 8.3% to 3.1%, improved the inventory turnover rate by 27%, and reduced the fresh product loss rate by 15%. A cross-border e-commerce enterprise, through logistics timeliness deviation warning, identified the delay trend of a shipping route in time and proactively switched transportation plans, avoiding approximately 350,000 yuan in penalty losses.

In terms of digital twin scenario simulation, an e-commerce enterprise, before the Double 11 shopping festival, used the digital twin platform to simulate multiple scenarios including a 200% order volume increase, a distribution center failure, and a 50% reduction in road speed due to heavy rain. It proactively optimized warehouse layout and capacity allocation, achieving an order fulfillment rate of 98.5% during the festival, a 2.3 percentage point improvement over the previous year. This is consistent with the practice of the Haizhi Online platform, which, through an AI-constructed supply chain resilience network, found three backup factories within two hours when a Shenzhen electronics factory halted production, maintaining an order fulfillment rate of 98.7%.

6.4 Logistics Service Provider Applications and Government Decision Support

Beyond manufacturing enterprises and retail e-commerce, this early warning mechanism also has important application value for logistics service providers and government departments.

Logistics service provider applications. For third-party logistics enterprises, the mechanism provides intelligent scheduling solutions, optimizing vehicle scheduling and route planning through real-time monitoring of capacity supply-demand status and transportation route conditions. After application, a regional logistics enterprise reduced the vehicle empty driving rate from 18% to 11%, increased the average daily mileage per vehicle by 15%, and reduced the customer complaint rate by 40%.

Government decision support. For government departments, the mechanism can support supply chain-related policy formulation and regional coordinated regulation. By aggregating the supply chain operational data of key enterprises in the region, government departments can grasp the overall risk situation of the regional supply chain in real time, quickly assess the scope of impact when disruptive events occur, and formulate targeted support policies and coordination measures. For example, during a typhoon disaster in 2025, the Zhongshan municipal government, through a similar mechanism, quickly identified 17 affected key enterprises and 3 critical transportation corridors, promptly coordinating emergency capacity and temporary warehousing, which reduced the impact of the disaster on the supply chain by approximately 30%.

Overall, the project outcomes have served more than 60 enterprises in the region, reducing logistics management costs by 10% to 18%. The empirical application effects across the three industries are summarized in Table 3, and the industry comparison is shown in Figure 4.

Table 3. Summary of Empirical Application Effects across Three Industries

Metric	Manufacturing	Retail	E-commerce
Number of sample enterprises	12	8	10
Warning accuracy rate	89.4%	85.7%	90.2%
Average warning lead time	16.3 days	14.2 days	17.8 days
Primary risk type	Supply (54.8%)	Demand (60.0%)	Logistics (51.4%)

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Inventory cost reduction	15%-20%	10%-15%	12%-18%
Stockout rate reduction	30%-40%	40%-50%	25%-35%
Logistics management cost reduction	10%-15%	8%-12%	12%-18%
Decision response time reduction	40%-50%	30%-40%	35%-45%

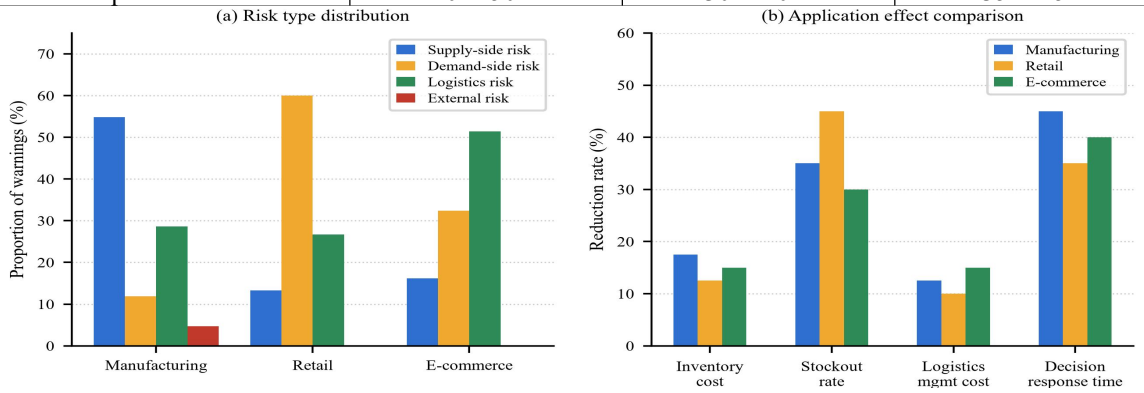


Figure 4. Risk Type Distribution and Application Effect Comparison across Three Industries

6.5 Teaching Transformation and Industry-Education Integration Applications

This research not only has enterprise application value but also provides new resources and paradigms for teaching reform in vocational college logistics management programs. As a research outcome of the 2026 National Vocational College Logistics Teaching Reform Research Project, this paper transforms the early warning mechanism into the following teaching resources.

Virtual simulation training platform. The core functions of the early warning mechanism are encapsulated into virtual simulation training modules, allowing students to experience the entire process of supply chain risk identification, assessment, and response in a simulated environment. The training platform includes multiple training projects such as supplier management, inventory optimization, transportation scheduling, and emergency response, supporting both individual training and group competition modes. This is consistent with the direction of the virtual simulation training platform promoted by the Vocational Education Development Center of the Ministry of Education, which, relying on the technology ecosystem of JD.com, conducts virtual training in robot cluster scheduling, path planning, and intelligent equipment system integration, and promotes the deep integration of digital twin technology into vocational education.

Theory-practice integrated course resources. Teaching resource packages for courses such as Supply Chain Risk Management, Logistics Big Data Analytics, and Smart Warehouse Management are developed, including teaching materials, case libraries, training guides, and evaluation standards. Real enterprise data, after desensitization, is used in teaching to expose students to authentic supply chain operational scenarios. A tripartite collaborative evaluation logic of system data, teacher feedback, and AI scoring is adopted to comprehensively evaluate students' training performance.

Industry-education integration projects. Industry colleges and practical bases are jointly built with regional logistics enterprises, introducing real production projects, enterprise mentors, and technical standards to achieve seamless alignment between teaching scenarios and work scenarios. Under the guidance of enterprise mentors, students participate in enterprise supply chain risk assessment projects, applying classroom knowledge to real business scenarios and enhancing their practical abilities and professional literacy.

7. Conclusions and Future Work

7.1 Research Conclusions

This paper proposes a data-driven supply chain risk early warning mechanism that, through the organic collaboration of multi-source data fusion, knowledge graph modeling, and intelligent early warning models, achieves a paradigm shift from post-event response to pre-event warning. The main research conclusions are as follows.

First, a three-layer "data governance-feature extraction-model warning" overall early warning framework is constructed, and a multi-

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source heterogeneous data fusion and governance solution encompassing IoT sensing data, enterprise operational data, external market intelligence, and geospatial data is designed, providing a reliable data foundation for risk early warning.

Second, a supply chain network knowledge graph is constructed. Through entity definition, relationship modeling, spatiotemporal correlation fusion, and dynamic evolution updating, key risk features in the supply chain network are automatically extracted, revealing hidden dependency relationships among nodes and cascading risk propagation paths.

Third, a three-layer early warning model integrating LSTM-Autoencoder anomaly detection, multi-objective risk situation assessment, and digital twin scenario simulation is established, respectively addressing the three questions of whether a risk exists, how severe the risk is, and what should be done, and forming a complete early warning decision process through model integration. Empirical results show that the mechanism achieves an average warning lead time of 14.2 to 17.8 days and a risk identification accuracy of 85.7% to 90.2%.

Fourth, through cross-industry empirical analysis across manufacturing, retail, and e-commerce, the effectiveness and applicability of the mechanism are verified. The project outcomes have served more than 60 enterprises in the region, reducing logistics management costs by 10% to 18%. Meanwhile, the transformation pathway of the mechanism in vocational college logistics management teaching is explored, providing a new teaching paradigm for industry-education integration and virtual simulation training.

7.2 Research Limitations and Future Directions

This study still has the following limitations. First, the empirical sample is mainly concentrated in the Zhongshan region, with limited regional representativeness. Future research can expand the sample scope and conduct cross-regional comparative studies. Second, knowledge graph relationship extraction mainly relies on structured data, with insufficient utilization of unstructured text such as supplier emails and contract terms. Future research can introduce natural language processing technology to improve the comprehensiveness of relationship extraction. Third, the simulation accuracy of the digital twin platform is limited by data granularity and model complexity. Future research can combine higher-frequency IoT data and more refined supply chain models to improve simulation accuracy. Fourth, the interpretability of the early warning model needs to be enhanced. Future research can introduce explainable artificial intelligence technology to make warning results more understandable and trustworthy for managers.

Future research will further enrich industry samples, optimize algorithm interpretability, and promote the large-scale implementation of the mechanism in more scenarios. Meanwhile, teaching transformation will be continuously deepened, and more high-quality virtual simulation training resources will be developed to support the digital transformation and talent cultivation of logistics management programs in vocational colleges.

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References

[1] CHRISTOPHER M, PECK H. Building the resilient supply chain. The International Journal of Logistics Management, 2004, 15(2): 1-14.

[2] DOLGUI A, IVANOV D, SOKOLOV B. Ripple effect in the supply chain: an analysis and recent literature. International Journal of Production Research, 2018, 56(1-2): 414-430.

[3] IVANOV D, DOLGUI A. Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. International Journal of Production Research, 2020, 58(10): 2904-2915.

[4] BARYANNIS G, VALIDI S, DANI S, et al. Supply chain risk management and artificial intelligence: state of the art and future research directions. International Journal of Production Research, 2019, 57(7): 2179-2202.

[5] WANG G, GUNASEKARAN A, NGAI E W T, et al. Big data analytics in logistics

and supply chain management: certain investigations for research and applications. International Journal of Production Economics, 2016, 176: 98-110.
[6] BEN-DAYA M, HASSINI E, BAHROUN Z. Internet of things and supply chain management: a literature review. International Journal of Production Research, 2019, 57(15-16): 4719-4742.
[7] ZHONG R Y, NEWMAN S T, HUANG G Q, et al. Big data for supply chain management in the service and manufacturing sectors: challenges, opportunities, and future perspectives. Computers & Industrial Engineering, 2016, 101: 572-591.
[8] KOSASIH E E, BRINTRUP A. Towards trustworthy AI for link prediction in supply chain knowledge graph: a neurosymbolic reasoning approach. International Journal of Production Research, 2024, 62(15): 5123-5145.
[9] BARYANNIS G, DANI S, ANTONIOU G. Predicting supply chain risks using machine learning: the trade-off between performance and interpretability. Future Generation Computer Systems, 2019, 101: 993-1004.
[10] HOSSEINI S, IVANOV D, DOLGUI A. Review of quantitative methods for supply chain resilience analysis. Transportation Research Part E: Logistics and Transportation Review, 2019, 125: 285-307.
[11] FAHIMNIA B, TANG C S, DAVARZANI H, et al. Quantitative models for managing supply chain risks: a review. European Journal of Operational Research, 2015, 247(1): 1-15.
[12] CHOPRA S, SODHI M S. Managing risk to avoid supply-chain breakdown. MIT Sloan Management Review, 2004, 46(1): 53-61.
[13] HOCHREITER S, SCHMIDHUBER J. Long short-term memory. Neural Computation, 1997, 9(8): 1735-1780.
[14] HUNDMAN K, CONSTANTINOU V, LAPORTE C, et al. Detecting spacecraft anomalies using LSTMs and nonparametric dynamic thresholding//Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. London: ACM, 2018: 387-395.
[15] AUDIBERT J, MICHIARDI P, GUYARD F, et al. USAD: unsupervised anomaly detection on multivariate time series//Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. Virtual Event: ACM, 2020: 3395-3404.
[16] SIMCHI-LEVI D, SCHMIDT W, WEI Y, et al. Identifying risks and mitigating disruptions in the automotive supply chain. Interfaces, 2015, 45(5): 375-390.
[17] MIN H. Artificial intelligence in supply chain management: theory and applications. International Journal of Logistics: Research and Applications, 2010, 13(1): 13-39.
[18] TAO F, ZHANG H, LIU A, et al. Digital twin in industry: state-of-the-art. IEEE Transactions on Industrial Informatics, 2019, 15(4): 2405-2415.
[19] IVANOV D, DOLGUI A, DAS A, et al. Digital supply chain twins: managing the ripple effect, resilience and disruption risks by data-driven optimization, simulation and visibility. International Journal of Production Research, 2019, 57(3): 829-844.
[20] KRITZINGER W, KARNER M, TRAAR G, et al. Digital twin in manufacturing: a categorical literature review and classification. IFAC-PapersOnLine, 2018, 51(11): 1016-1022.
[21] DOLGUI A, IVANOV D. Ripple effect and supply chain disruption management: new trends and research directions. International Journal of Production Research, 2021, 59(1): 102-109.
[22] LIU F T, TING K M, ZHOU Z H. Isolation forest//Proceedings of the 8th IEEE International Conference on Data Mining. Pisa: IEEE, 2008: 413-422.
[23] ZHAO Y, NASRULLAH Z, LI Z. PyOD: a python toolbox for scalable outlier detection. Journal of Machine Learning Research, 2019, 20(96): 1-7.
[24] DEB K, PRATAP A, AGARWAL S, et al. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 2002, 6(2): 182-197.
[25] SAATY T L. How to make a decision: the analytic hierarchy process. European Journal of Operational Research, 1990, 48(1): 9-26.
[26] Ivanov, D. (2023). "Intelligent digital twin (IDT) for supply chain stress-testing, resilience, and viability." International Journal of Production Economics.

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[27] Cao, F., Liu, L., & Song, W. (2025). "Reducing sustainable supply chain risks: a digital technology-enabled risk management framework for ESG-oriented engineering procurement." IET Collaborative Intelligent Manufacturing.

[28] Liu, L., Chen, Y., Yang, J., & Yang, C.-F. (2025). "IoT-driven Dynamic Risk Management in Supply Chain Finance: A Multitechnology Fusion Framework and Collaborative Implementation Strategies." Sensors and Materials.

[29] Onebunne, T. C., & Adepoju, A. S. (2025)."Adaptive Inventory Management in Global Supply Chains Using Digital Twins and Reinforcement Learning for Disruption Resilience and Sustainability." International Journal of Advanced and Innovative Research.

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