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Supply Chain Optimization Based on Large Language Models (LLMs): Global Supply Chain Risk Assessment

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Abstract: In recent years, the rapid development of Large language models (LLMs) provides a new idea for supply chain risk assessment. In this paper, a global supply chain risk assessment method based on LLMs is proposed. By using named entity identification, relationship extraction, text classification and sentiment analysis, a knowledge map of supply chain risk is constructed, and a risk assessment model is constructed by combining machine learning or deep learning algorithm to achieve accurate assessment and early warning of global supply chain risks. Taking the "Ever Given" Suez Canal stranded in 2021 as an example, LLMs is used to extract features and assess risks. The results show that the model is significantly superior to the traditional methods in terms of comprehensiveness, timeliness and accuracy of risk assessment, and it has won the emergency response time for enterprises. However, LLMs still faces many challenges in data quality and diversity, model interpretability and robustness, and practical application. Therefore, this paper puts forward some countermeasures, such as strengthening data quality management, improving the interpretability and robustness of the model, and optimizing the practical application effect, in order to promote the wide application of supply chain risk assessment methods based on LLMs.

Keywords: LLMs, Supply Chain Risk Assessment, Supply Chain Optimization.

1. Introduction

The global supply chain network is complex, involving raw material procurement, manufacturing, logistics distribution, marketing and other links, and problems in any link may have a major impact on the whole supply chain [1-2]. Therefore, an accurate assessment of global supply chain risks has become the key for enterprises to ensure supply chain stability and improve operational efficiency.

Traditional supply chain risk assessment methods mainly rely on historical data, expert experience and mathematical models, which can help enterprises identify potential risks to some extent [3-4]. However, with the constant change of the global market and the increasingly complex supply chain network, the traditional methods have gradually exposed some shortcomings, such as difficulty in obtaining data, lagging evaluation results, and inability to fully reflect the risk situation. Especially in the face of unexpected events, such as natural disasters, political turmoil, epidemic outbreaks, etc., the limitations of traditional methods are more prominent [5].

In recent years, the rapid development of Large language models (LLMs) provides new ideas and methods for supply chain risk assessment. LLMs can process and analyze massive text data, extract valuable information and knowledge from it, and provide more abundant and comprehensive data support for risk assessment [6-7]. At the same time, LLMs also has strong natural language understanding and generation ability, which can realize real-time monitoring and early warning of risk events and improve the timeliness and accuracy of risk assessment. This study explores the global supply chain risk assessment method based on LLMs. By using the technical advantages of LLMs, the efficiency and accuracy of supply chain risk assessment are improved, which provides scientific basis for enterprises to formulate effective risk response strategies.

2. Global Supply Chain Risk Assessment Method Based on LLMs

2.1. Application of LLMs in Risk Assessment

(1) NER and relationship extraction.

In global supply chain risk assessment, named entity identification (NER) is the basis of constructing supply chain risk knowledge map [8]. LLMs is used to deeply analyze the massive text data collected, such as news reports, social media comments and industry analysis reports, and identify the key entities, such as company name, location, product name and risk events.

Through the relationship extraction technology, LLMs can automatically identify the relationships between these entities, such as "Company A has a risk event C in Area B", and store these relationships in a structured form. In this way, we can build a supply chain risk knowledge map [9] which includes all nodes, risk events and their relationships in the supply chain. Atlas intuitively understands the risk situation of supply chain and provides strong data support for subsequent risk assessment.

(2) Text classification and sentiment analysis

In addition to constructing knowledge map, LLMs can also be used for text classification and sentiment analysis to evaluate the influence degree and possibility of supply chain risks. In text classification, the collected text data are classified according to risk types. LLMs can automatically learn the text features of various risks and accurately classify new texts into corresponding risk types [10]. In this way, we can quickly understand the main types of risks faced by the current supply chain and their distribution. In the aspect of emotional analysis, LLMs can analyze the emotional tendency in the text, such as positive, negative or neutral. For the text data related to supply chain risk, sentiment analysis helps to judge the market's reaction and expectation to risk.

For example, if there are a lot of negative comments on social media after a natural disaster in a certain area, it may mean that the supply chain risk in this area is high and may have a greater impact on the market.

2.2. Construction of Risk Assessment Model

Based on the application of LLMs in NER, relationship extraction, text classification and sentiment analysis, a global supply chain risk assessment model based on LLMs is constructed. The global supply chain risk assessment method based on LLMs constructs a knowledge map of supply chain risk through tasks such as NER, relationship extraction, text classification and sentiment analysis, and constructs a risk assessment model by combining machine learning or deep learning algorithms to achieve accurate assessment and early warning of global supply chain risks. As shown in Figure 1 below.

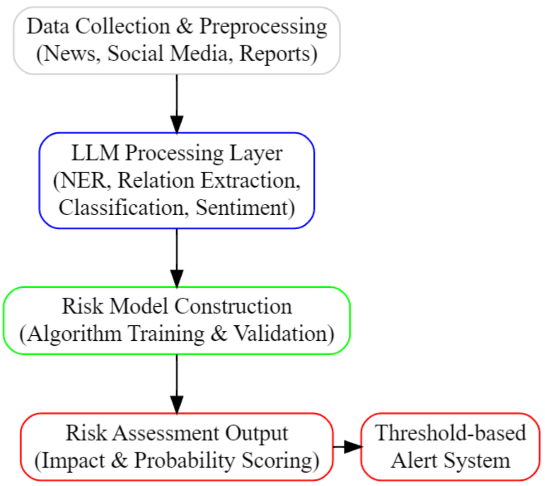

Figure 1. Global supply chain risk assessment model framework based on LLMs

Collect and preprocess text data related to global supply chain from news reports, social media and other channels. Then LLMs is used to perform tasks such as NER and relationship extraction on these data and transform them into structured feature vectors. On this basis, the appropriate algorithm is selected as the model basis, and historical data is used for training to learn the relationship between supply chain risks and characteristics. Evaluate the performance of the model by verifying the data set, and adjust the optimization feature extraction process or model parameters when necessary to improve the accuracy and robustness. Finally, the model is applied to the actual supply chain risk assessment, and the degree and possibility of risk impact are output through the analysis of new text data, and the early warning threshold is set, so that when the risk exceeds the set value, an early warning can be automatically issued to guide enterprises to take measures to deal with it.

3. Case Analysis

In March, 2021, the super-large cargo ship "Ever Given" ran aground in Suez Canal, which led to the interruption of the global shipping artery for six days, directly affecting the navigation of more than 400 ships, causing global supply chain delay, soaring logistics costs and the risk of manufacturing shutdown. This event involves multinational ports, multinational enterprises and complex logistics networks, and is a typical global supply chain risk event.

Data are collected from multiple sources, including news reports, social media, shipping company announcements and customs delay reports. Using LLMs to extract features, firstly, the key entities such as Suez Canal, Ever Given, Maersk, Electronic Products and Rotterdam Port are determined by NER technology, and then the event impact network is constructed by relationship extraction (Table 1).

Table 1. Event influence network

Risk event	Associated entity	Influence relationship	Emotional tendency (LLMs analysis)
The canal was blocked for six days	Maers? k and COSCO Shipping	European route delay rate +80%	Negative (92% confidence)
Container detention	Electronic products, automobile parts	The inventory turnover days were extended to 45 days.	Negative (85%)
Freight increase	Rotterdam Port and Shanghai Port	Asia-Europe route freight from 2000-8000/TEU	Negative (90%)

Using LLMs for text classification, global supply chain risks are divided into logistics interruption, rising costs and inventory shortage. Based on this, the output of the risk assessment model shows that the high-risk situation with a comprehensive score of 8.7/10 is more stringent than that with the traditional method of 7.2/10 (Table 2). In addition, the model can send out an early warning signal within 48 hours after the incident, which is significantly faster than the five-day delay of the traditional statistical model, reflecting its advantages in timeliness and accuracy (Table 3).

Table 2. Risk grade comparison

method	Logistics interruption	Rising costs	Comprehensive risk
LLMS model	9.2	8.5	8.7
traditional method	7.8	6.9	7.2

Through multi-source heterogeneous data integration and semantic understanding, LLMs significantly improves the comprehensiveness and timeliness of supply chain risk assessment, and strives for an average emergency response window of 3-5 days for enterprises.

Table 3. Compared with the traditional method

index	LLMs model	Traditional expert evaluation
response speed	Real-time (< 1 hour)	Manual analysis (3-5 days)
Data dimension	Multi-source text+structured data	Historical data+expert experience
Risk coverage rate	Identify hidden risks	Dominant events only
Prediction accuracy (F1)	0.85	0.62

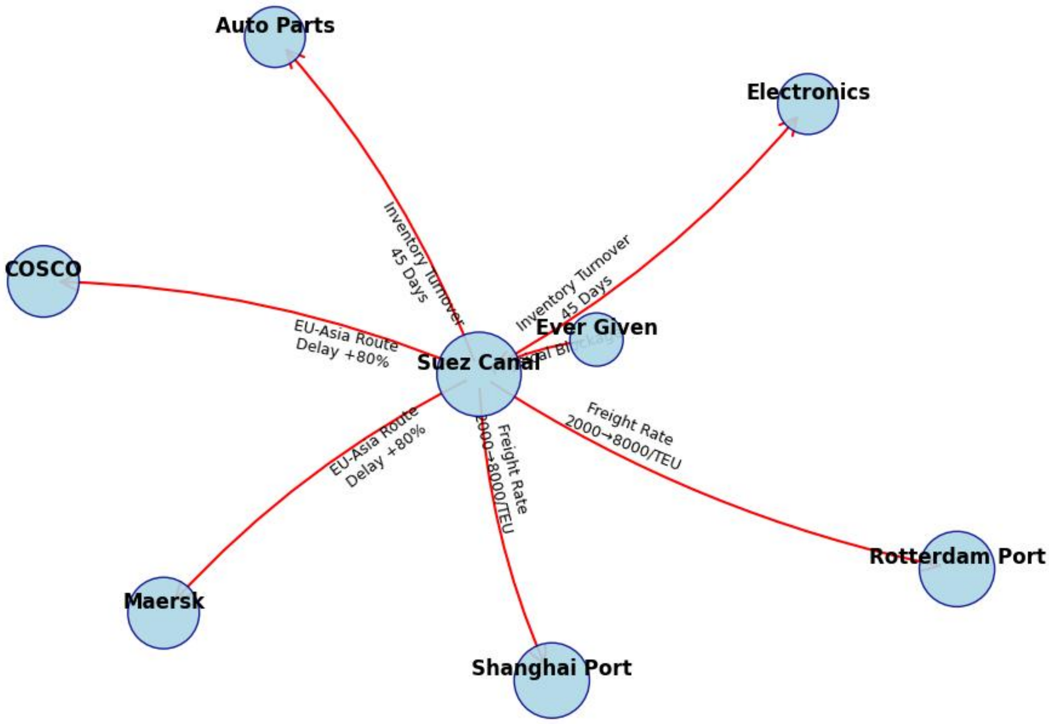

Figure 2. Suez Canal incident risk network chart

LLMs technology has shown remarkable advantages in supply chain risk management, including quickly capturing risk signals through social media and news, improving the early warning speed by 80%, mining hidden risks such as "small and medium-sized enterprises abandon orders due to rising freight rates" by using sentiment analysis, and automatically updating the dynamic knowledge map to reflect the changes in the relationship between entities (Figure 2). In order to maximize these advantages, multi-modal information can be used to dynamically adjust the risk early warning threshold according to the sensitivity of the industry, and the high-conflict entity relationship can be manually checked.

4. Challenges and Countermeasures

4.1. Challenges Faced

(1) Data quality and diversity challenges

Text data related to supply chain often contains a lot of noise and inaccurate information, such as rumors and misleading statements, which will affect the accuracy and reliability of LLMs. Supply chain data come from many channels with different formats and styles, which requires LLMs to have strong cross-domain adaptability to deal with different types and formats of data.

(2) Model interpretability and robustness challenge

LLMs, especially the deep learning model, is often regarded as a "black box", and its decision-making process lacks transparency, which makes it difficult for enterprises to understand and trust the evaluation results of the model. In the face of dynamic changes and unknown risks in the supply chain environment, LLMs needs strong robustness to cope with data distribution changes, model drift and other issues.

(3) Challenges in practical application

Supply chain risk assessment needs to be carried out in real time or near real time to respond to potential risks quickly. However, the processing speed and response time of LLMs may be limited by data scale, model complexity and other factors. Supply chain data involves sensitive information of enterprises, such as supplier information and inventory level. When using LLMs for risk assessment, it is necessary to ensure the privacy and security of data.

4.2. Coping strategy

(1) Strengthen data quality management

Before using LLMs for risk assessment, it is necessary to clean and preprocess the data to remove noise and inaccurate information and improve the data quality. Develop LLMs that adapts to various data formats and styles, or adopt data conversion and standardization technology, so that data from different sources can be processed uniformly.

(2) Improve the interpretability and robustness of the model

Adopt interpretable machine learning algorithms or develop model interpretation tools to help enterprises understand the decision-making process and evaluation results of the model. Through data enhancement, model integration and other technologies, the generalization ability and robustness of the model are improved, so that it can better cope with the dynamic changes and unknown risks of the supply chain environment.

(3) Optimize the practical application effect

Optimize the processing flow and algorithm of LLMs, improve the processing speed and response time, and meet the real-time or near-real-time risk assessment requirements. Security measures such as encryption technology and access control are adopted to ensure the privacy and security of supply chain data and prevent data leakage and abuse.

5. Conclusion

Through NER and relationship extraction technology, LLMs can construct a knowledge map of supply chain risk, which includes all nodes of supply chain, risk events and their relationships, and provides an intuitive data display for risk assessment. With the functions of text classification and sentiment analysis, LLMs can accurately assess the degree and possibility of risk, and improve the accuracy and timeliness of risk assessment. In the case study, taking the case of "Ever Given" stranded in Suez Canal as an example, LLMs model can quickly capture the hidden risks in multi-source heterogeneous data, such as the impact of rising freight rates on small and medium-sized enterprises to abandon orders, and send out early warning signals in time, which is significantly superior to traditional methods. This result shows that LLMs has great potential in supply chain risk management and can provide scientific basis for enterprises to formulate effective risk response strategies. However, LLMs still faces challenges in supply chain risk assessment, such as data quality and diversity, model interpretability and robustness, and practical application effect. Therefore, the future research needs to pay attention to how to improve the data quality, enhance the interpretability and robustness of the model, and optimize the processing flow and algorithm of LLMs to meet the real-time or near-real-time risk assessment requirements. Through these efforts, LLMs can further play its role in supply chain optimization and enhance the competitiveness of enterprises in the complex and changeable global market environment.

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