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# Research on the Application of Large Models in Supply Chain Management

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## ABSTRACT

With the rapid advancement of artificial intelligence technology, large language models (LLMs) are emerging as a revolutionary productivity tool, profoundly reshaping traditional operational paradigms in the field of supply chain management. This paper systematically examines the application value, implementation pathways, and future trends of LLM technology in supply chain management. Research indicates that LLMs, by leveraging their powerful capabilities in data processing, pattern recognition, and predictive analytics, demonstrate significant advantages in core supply chain processes such as demand forecasting, inventory optimization, supplier management, and logistics distribution. These capabilities enable precise market insights, real-time dynamic adjustments, and intelligent decision-making support. The study further highlights that the application of LLMs in the supply chain domain still faces multiple challenges, including data quality, privacy and security, technical implementation, and cost-effectiveness, necessitating targeted strategies for mitigation. Looking ahead, as the technology continues to mature and the ecosystem improves, LLMs are expected to drive supply chain management toward greater intelligence, collaboration, and sustainability, thereby creating substantial value for enterprises.

## KEYWORDS

Large models; Supply chain management; Artificial intelligence; Demand forecasting; Inventory optimization; Intelligent decision-making

## 1. INTRODUCTION

Supply chain management, as a core component of enterprise operations, directly influences key performance indicators such as product quality, cost control, and market responsiveness. Traditional supply chain management models often rely on historical experience, manual judgment, and basic data analysis tools. When confronted with complex and volatile market conditions, these approaches frequently exhibit shortcomings such as delayed response, forecasting inaccuracies, and low efficiency [1]. Against the backdrop of global economic integration and increasingly diverse consumer demands, supply chain management now faces unprecedented challenges and opportunities.

In recent years, breakthrough advancements in artificial intelligence, particularly in large language model (LLM) technology, have provided new solutions for the digital transformation of supply chain management. LLMs refer to deep neural network models comprising millions or even billions of parameters, which, after specialized training, can process and utilize massive datasets for complex tasks. These models exhibit not only powerful capabilities in natural language processing and image recognition but also demonstrate exceptional performance in multimodal data fusion, predictive analytics, and decision-making optimization. Since 2023, China's LLM industry has experienced explosive growth. Leading logistics enterprises such as SF Express, JD Logistics, and Cainiao have successively launched their own logistics-focused LLMs, leveraging AI technologies to drive down costs, improve efficiency, and foster business innovation.

This paper aims to systematically investigate the current application landscape, key technologies, and future trends of LLMs in supply chain management. It will analyze their specific implementations in critical areas such as demand forecasting, inventory management, supplier selection, and logistics optimization. Furthermore, the study will discuss the existing challenges and potential countermeasures, intending to serve as a valuable reference for enterprises and research institutions in this field.

# 2. THE ALIGNMENT BETWEEN LARGE LANGUAGE MODEL TECHNOLOGY AND SUPPLY CHAIN MANAGEMENT

Large language model (LLM) technology is built upon deep learning frameworks, utilizing the Transformer architecture. Trained through unsupervised or self-supervised learning on massive datasets, it excels at extracting deep-seated patterns and feature representations from complex data. Compared to traditional artificial intelligence models, LLMs exhibit distinctive characteristics such as vast parameter scales, strong generalization capabilities, and cross-modal processing abilities [2]. These technical attributes make LLMs particularly well-suited to address the complex demands of supply chain management.

Fundamentally, supply chain management involves the operation of a complex system with multiple links, numerous stakeholders, and often competing objectives. From a data perspective, the massive data generated within supply chains includes both structured data (e.g., order records, inventory levels) and unstructured data (e.g., supplier evaluations, contract texts). This data is characterized by diverse sources and complex formats, making it difficult for traditional tools to fully exploit its value [3]. LLMs, capable of processing multiple data types simultaneously—including text, images, audio, and video—can provide a more comprehensive understanding of operational contexts in logistics scenarios. For instance, by integrating order text, vehicle images, and equipment audio, they offer a richer information base for decision-making.

From a decision-making standpoint, supply chain management must contend with various uncertainties, including fluctuations in market demand, supplier risks, and logistics disruptions [4]. Having undergone extensive pre-training, LLMs possess powerful learning capabilities that enable them to discern patterns within data. Through fine-tuning, they can be quickly adapted to specific tasks and data characteristics in the logistics domain. Even when confronted with novel scenarios or data patterns, LLMs can perform reasonable inference and support decision-making, thereby helping to manage the dynamic nature of supply chains effectively.

The application of LLMs in supply chains can be categorized across multiple levels. At the most basic operational level, they can automate repetitive tasks such as order entry and data verification. At the tactical level, LLMs can optimize inventory management and transportation routes. At the strategic level, they can contribute to supply chain network design and long-term planning. This multi-tiered applicability positions LLM technology as a core driver for the digital transformation of supply chains.

# 3. PRACTICAL APPLICATIONS OF LARGE LANGUAGE MODELS IN KEY SUPPLY CHAIN PROCESSES

## 3.1. Demand Forecasting and Inventory Management

Demand forecasting serves as the cornerstone of supply chain management, directly influencing inventory levels, production planning, and logistics arrangements [5]. Traditional forecasting methods, often reliant on time-series analysis and small-scale machine learning models, struggle to process large-scale, multi-source data and capture subtle market shifts. In contrast, large AI models can integrate and analyze diverse information sources, including historical sales records, macroeconomic data, industry trends, social media sentiment, and weather forecasts. Through deep mining and analysis of this data, they excel at identifying nuanced changes in market demand and underlying trends.

In the consumer electronics industry, for instance, enterprises can leverage discussions on social media regarding the popularity of new technological features, combined with historical sales data, to predict consumer preferences and approximate demand volumes for next-generation products. For different customer segments, regions, or even sales channels, large AI models can generate personalized demand forecasts based on their respective characteristics and historical data. Given the dynamic nature of market conditions, these models continuously update and analyze data, allowing for timely adjustments to demand predictions. When confronted with unforeseen public events or fluctuations in raw material prices, the models can rapidly assess the impact of these factors on market demand. This provides enterprises with accurate and timely forecasts, enabling swift adjustments to production and supply chain strategies [6].

In inventory management, large AI models synthesize data from demand forecasts, procurement lead times, production plans, and other relevant factors. Utilizing sophisticated algorithms and simulations, they calculate optimal inventory levels. Based on characteristics such as sales velocity and demand variability, the models help formulate differentiated inventory strategies for different products and materials. This approach mitigates the risks of both overstocking and stockouts, thereby reducing inventory costs and minimizing capital tied up in stock [7].

Industry practices demonstrate these applications. JD Logistics has leveraged large model technology to launch Jinghui 3.0, an integrated digital supply chain data management platform. It offers functions like sales forecasting, inventory alerts, and intelligent replenishment, assisting clients in optimizing supply chain planning to reduce costs and improve efficiency. Similarly, Cainiao Supply Chain has released "Tianji π," a digital supply chain product based on large models. By integrating operations research with AI and big data, it automatically generates demand plans based on sales forecasts, inventory plans via global optimization, replenishment plans using intelligent allocation, and production schedules through operational research optimization. This enables enterprises to transition their supply chain management focus from simply "having a plan" to "having an effective plan."

### 3.2. Supplier Management and Risk Assessment

Supplier management constitutes a critical link in supply chain management, directly impacting the quality, cost, and stability of raw material supply [8]. AI large language models (LLMs) can collect and analyze vast amounts of supplier data—including financial status, production capacity, quality control metrics, delivery records, and industry reputation—to construct comprehensive supplier risk assessment models. Through continuous monitoring and analysis of this data, LLMs enable early warnings of potential risks that suppliers may encounter.

Based on a company's specific requirements and the comprehensive capabilities of potential suppliers, AI LLMs can rapidly screen and identify the most suitable candidates by comparing and analyzing extensive supplier datasets. During the selection process, the models evaluate multiple dimensions such as product quality, price, delivery timelines, and technical capabilities. These factors are weighted according to the enterprise's strategic objectives and procurement needs, thereby providing data-driven optimal supplier selection recommendations.

Furthermore, leveraging AI LLMs enables continuous performance evaluation of suppliers. Utilizing key indicator data—including on-time delivery rates, product quality consistency, and after-sales service levels—the models regularly score and rank suppliers. Analysis of this performance data helps enterprises collaboratively identify improvement measures with suppliers, optimize cooperative processes, and enhance the overall efficiency and quality of the supply chain [9].

### 3.3. Logistics Distribution and Route Optimization

Logistics distribution is a critical execution link in the supply chain, directly impacting customer experience and operational costs [10]. Large language models (LLMs) can provide optimal route recommendations for transport vehicles by analyzing real-time factors such as traffic conditions and weather. Furthermore, AI LLMs can automatically adjust vehicle loading sequences and delivery priorities based on order urgency and destination addresses, thereby significantly enhancing distribution efficiency.

Baidu Map, leveraging its foundational LLM capabilities and tailored specifically for the logistics industry, has launched a Beta version of its Logistics Large Model. In the domain of address parsing, the model utilizes the strengths of LLMs in Chinese semantic understanding and knowledge enhancement. By deeply mining Baidu Map's POLI big data and logistics waybill address data, it effectively handles complex, non-standardized text to perform various tasks. These include address content recognition, analysis of geographical relationships, address verification and error correction, coordinate resolution, and similarity assessment between addresses. Regarding scheduling decisions, the model is fine-tuned based on the architecture of large models and trained within a reinforcement learning framework. This enables end-to-end inference, outputting decision results optimized for various logistics scenarios such as vehicle scheduling, load planning and container stuffing, and warehouse location selection. Comparative evaluations indicate that this approach reduces cost metrics by over 3% and decreases computation time by more than 90% compared to traditional heuristic algorithms.

SF Technology(a subsidiary of SF Express) has introduced "Fengzhi," a large model designed for logistics decision-making. It is primarily applied in intelligent analysis, sales forecasting, transportation route optimization, and packaging optimization within the logistics supply chain. To address the challenge of deploying large models in practical supply chain operations, SF Technology has developed a Supply Chain Agent. This agent, built upon SF's Fengzhiyun ecosystem, can precisely identify the reasons behind fluctuations in a client's sales volume, providing managers with a decision-making basis and assisting them in selecting appropriate response strategies.

### 3.4. Supply Chain Collaboration and Decision Support

As a shared intelligent platform, large language models (LLMs) can integrate data and information from various departments—including procurement, production, sales, and logistics—breaking down information silos and fostering cross-departmental collaboration. Through the analytical and predictive outputs of the model, different departments can better understand the needs and plans of others, enabling proactive preparation and coordination, thereby enhancing the overall efficiency of the supply chain.

Based on in-depth analysis of end-to-end supply chain data and accurate predictions of market trends, AI LLMs provide strategic decision support for senior enterprise management. When considering major decisions such as entering new markets, investing in new production lines, or optimizing supply chain networks, the LLM can simulate supply chain performance under different scenarios. This provides managers with a robust basis for decision-making, supporting the development of more scientific and rational strategic plans.

When disruptive events occur within the supply chain, AI LLMs can rapidly analyze the scope and severity of the impact and recommend appropriate response strategies. Leveraging predefined rules and historical data, the model can automatically generate contingency plans and coordinate actions among relevant departments to minimize the disruption's negative effects.

JD Industrials' large model, Joy Industrial, utilizes multi-agent collaboration to create "thinking supply chain experts," driving the digital and intelligent transformation of the supply chain. Based on scaling laws, the model selected the smallest viable LLM size expected to deliver results for industrial applications. Employing a Teacher-Student (T-S) model training strategy, a larger teacher model's knowledge was distilled into a smaller, more efficient student model. This approach significantly reduces training, deployment, and inference costs while maintaining performance close to that of the larger model. Ultimately, the post-training resource requirements for the Joy Industrial LLM are only 1/16th of those for a general-purpose LLM.

# 4. APPLICATION CHALLENGES AND RESPONSE STRATEGIES

## 4.1. Data Quality and Privacy Security Issues

Large language models face significant challenges related to data quality and privacy security in their application within supply chains.The training of LLMs requires vast amounts of high-quality data. However, within the logistics industry, the collection, processing, and utilization of data present challenges concerning privacy protection and data security. The industrial manufacturing sector comprises numerous specialized sub-fields, each with significant differences in production processes, techniques, production line configurations, and types of raw materials and products. This diversity makes the collection, utilization, and development of manufacturing process data particularly difficult. Data confidentiality during production is paramount, leading to predominantly private databases with limited data scale. Consequently, LLMs suffer from a lack of high-quality, massive learning samples, which constrains their autonomous learning process. Furthermore, data training can introduce issues of "data pollution" and leakage. Feeding poor-quality industrial data can cause "data pollution" in LLMs, while the cross-enterprise and cross-industry circulation of data raises risks such as secure transmission and the leakage of commercial secrets.

To address these challenges, enterprises need to establish comprehensive data governance frameworks. These should include data quality standards, data security protocols, and data sharing mechanisms. Technologies such as federated learning and blockchain can be adopted to enable multi-party data collaboration while protecting data privacy. It is essential to organize enterprises and research institutions from both the supply and demand sides of LLMs to jointly develop standardized specifications for industrial LLM training data. Deepening the application of technologies like blockchain and federated learning in industrial data circulation is crucial. Encouraging medium and large manufacturing enterprises to openly share anonymized operational data can help establish extensive industrial corpora and data resource pools, providing the necessary data foundation for training robust LLMs.

## 4.2. Technical Implementation and Cost-Benefit Challenges

The effective integration of large language model technology with existing logistics and supply chain systems to achieve data-driven decision-making and optimization presents significant technical implementation challenges. The industrial sector involves a wide variety of technologies, including diverse equipment, industrial software, control objects, protocols, and network structures. Among these, industrial software plays a crucial connecting role in bridging LLMs with industrial applications.

Currently, there is still a gap between the technical level of domestic industrial software and its foreign counterparts, which, to some extent, restricts the depth of integration and the pace of adoption of LLMs in the industrial sector. The application of LLMs in industry requires vast industrial datasets and high-performance computing clusters for training, leading to high power consumption and substantial costs for both training and inference. Furthermore, the return on investment for their use in the industrial field remains unclear, which somewhat limits enterprises' motivation for adoption.

To reduce technical implementation difficulty and improve cost-effectiveness, enterprises can adopt a gradual implementation strategy. This involves starting with scenarios where pain points are obvious and benefits are easily measurable, then progressively expanding the scope of application. From a technical perspective, adopting lightweight and scenario-specific model designs can help reduce computational resource requirements.

### 4.3. Talent Shortage and Organizational Resistance to Change

The application of large language models in supply chains faces challenges beyond technology, primarily manifested in talent shortages and organizational resistance to change. As an emerging technology, there is a relative scarcity of professionals proficient in LLMs, and individuals with dual expertise in both LLM technology and supply chain management are particularly rare. This talent gap creates significant difficulties in recruitment and training when enterprises seek to adopt LLM technology.

Furthermore, the introduction of LLMs often necessitates corresponding organizational restructuring and process transformations, which may encounter internal resistance. These human factors and organizational cultural elements can become significant invisible barriers to the effective implementation of LLMs.

To address these challenges, enterprises need to strengthen talent development and recruitment, establishing cross-functional implementation teams that include data scientists, supply chain experts, and business representatives. Simultaneously, strong executive support and clear change management plans are essential to help employees understand the value and impact of LLMs. Gradually fostering a data-driven culture, breaking down departmental silos, and promoting data sharing and collaborative decision-making are crucial steps forward.

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