ISSN 2616-5902 Vol. 7, Issue 2: 132-139, DOI: 10.25236/AJBM.2025.070218

Research on Supply Chain Logistics Prediction and Decision Optimization Driven by Artificial Intelligence

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Abstract: *With the rapid development of artificial intelligence technology, its application in supply chain management has gradually become an important means to improve efficiency and optimize decision-making. This study focuses on supply chain logistics prediction and decision optimization driven by artificial intelligence, analyzing the application of artificial intelligence technologies such as machine learning, deep learning, and data mining in the logistics field. Through research on demand forecasting, inventory management, transportation scheduling, and other aspects, this article finds that artificial intelligence can effectively improve the accuracy of forecasting, optimize the decision-making process, thereby reducing costs, improving response speed, and enhancing the flexibility of the supply chain. At the same time, this study also explores the challenges faced in practical applications, such as data quality, system integration, and technical costs, and proposes corresponding solutions. Finally, this paper looks forward to the development trend of artificial intelligence in future supply chain logistics management, and believes that with the further maturity of technology, artificial intelligence will play an increasingly important role in various links of the supply chain.*

Keywords: *artificial intelligence, supply chain management, logistics forecasting, decision optimization*

1. Introduction

Against the backdrop of rapid globalization and informatization, supply chain management, as an important component of modern enterprise operations, is facing unprecedented challenges. How to effectively predict demand, optimize inventory management, improve transportation efficiency, and achieve coordinated operation of the overall supply chain in a complex and ever-changing market environment has become a key factor in enterprise competitiveness. Although traditional supply chain management methods can partially meet routine needs, they are often limited by low efficiency and insufficient flexibility when dealing with large-scale dynamic market environments. In order to address these challenges, more and more enterprises are seeking technological innovation, especially the application of artificial intelligence (AI) technology, to enhance the intelligence level of supply chains and promote the transformation and upgrading of supply chain management.

The rapid development of artificial intelligence, especially machine learning, deep learning, and reinforcement learning technologies, has provided new solutions for supply chain management [1]. These technologies can achieve accurate prediction of demand changes, optimization control of inventory levels, and intelligent decision-making of logistics paths by processing massive amounts of data, thereby greatly improving the accuracy and efficiency of supply chain management. For example, machine learning models can predict future demand fluctuations through historical data analysis, deep learning models can identify potential patterns in complex multidimensional data environments, and reinforcement learning helps businesses make optimal choices in the face of uncertainty by simulating and optimizing dynamic decision-making processes. Despite the enormous potential of artificial intelligence in supply chain management, existing research and applications still face many challenges. These challenges are mainly reflected in ensuring data quality, adapting algorithms, real-time decision-making processes, and interpretability of models. In order to effectively address these issues, enterprises need to solve a series of practical problems such as how to integrate different types of data, optimize algorithm models, and achieve cross departmental collaboration when applying artificial intelligence technology. Therefore, this study aims to explore the application of artificial intelligence

ISSN 2616-5902 Vol. 7, Issue 2: 132-139, DOI: 10.25236/AJBM.2025.070218

technology in supply chain logistics prediction and decision optimization, with a focus on how to solve practical problems in supply chain management through innovative methods, and provide valuable references for theory and practice.

Through the conduct of this study, it is expected to provide new ideas for the academic and business communities, promote the deep integration of artificial intelligence technology in supply chain management, and provide theoretical basis and practical guidance for the intelligent development of future supply chains.

2. Literature review and theoretical basis

With the complexity of global supply chain networks and the variability of market environments, supply chain management has gradually become a core component of enterprise competitiveness. In the past few decades, the field of supply chain management has undergone a gradual evolution from traditional methods to modern technology driven approaches, especially with the introduction of artificial intelligence (AI) technology, which has brought profound changes to supply chain logistics management [2].

2.1 Traditional methods in supply chain logistics management

As an interdisciplinary field, supply chain logistics management has traditionally relied on experience driven decision-making methods and rule-based models to optimize logistics and supply chain operations [3]. Among these traditional methods, the most common ones include inventory control based management methods, demand forecasting models, and transportation optimization methods.

In terms of inventory management, traditional inventory management methods typically rely on historical demand data and simple forecasting models, using economic order quantity (EOQ), periodic ordering systems (R, Q), and other methods to control inventory levels. The advantage of these methods is that they are easy to operate and can ensure the smooth operation of the supply chain in a relatively stable market environment. However, with the increasing volatility of market demand and the complexity of supply chain networks, traditional inventory management methods often appear inadequate in the face of uncertainty. Traditional demand forecasting methods mainly rely on statistical methods based on time series, such as exponential smoothing and ARIMA models. These methods predict future demand by analyzing historical sales data. However, these methods often fail to capture the rapid changes in demand when facing highly uncertain and rapidly changing market environments, resulting in significant prediction errors and subsequently affecting the accuracy of supply chain decisions.

In terms of transportation management, traditional logistics optimization methods usually use mathematical modeling techniques such as linear programming and integer programming to minimize transportation costs and optimize routes. However, these methods often overlook the dynamic uncertainties that exist during the transportation process (such as weather changes, traffic congestion, etc.), and when dealing with complex, cross-border supply chains, the computational workload is huge and the efficiency is low. Although these traditional methods have provided guidance for supply chain management to some extent, their limitations are gradually exposed in the face of modern complex and dynamic market environments, especially in dealing with big data analysis and intelligent decision-making. Traditional methods appear relatively lagging behind.

2.2 Current application status of artificial intelligence in supply chain logistics

The rapid development of artificial intelligence (AI) technology, especially machine learning (ML), deep learning (DL), reinforcement learning (RL) and other technologies, has brought new opportunities for supply chain logistics management. Artificial intelligence, through its powerful data processing capabilities and adaptive learning characteristics, can significantly improve the prediction accuracy, decision-making efficiency, and flexibility of the supply chain.

In demand forecasting, the application of artificial intelligence technology has gradually replaced traditional statistical methods. For example, machine learning algorithms can discover deeper patterns of demand changes and make more accurate predictions by training on large amounts of historical data. Especially in markets with significant demand fluctuations or cyclical changes, artificial intelligence

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algorithms have shown stronger adaptability. For example, demand forecasting models based on algorithms such as Support Vector Machine (SVM) and Random Forest (RF) can achieve high prediction accuracy in practical applications. Meanwhile, the application of artificial intelligence technology in inventory management is mainly reflected in optimizing inventory levels through real-time data monitoring and intelligent scheduling. For example, intelligent prediction systems based on deep learning can dynamically adjust inventory based on multidimensional data such as market demand, production planning, and supply situation, avoiding the occurrence of excessive inventory or stockouts. Reinforcement learning algorithms are also used in the dynamic decision-making process of inventory management, by simulating and optimizing inventory management strategies, improving inventory turnover and reducing inventory costs.

The application of artificial intelligence in transportation management is mainly reflected in path optimization, real-time scheduling, and dynamic transportation strategies. The application of reinforcement learning in logistics path selection can achieve optimal transportation route selection under complex traffic, weather, and transportation constraints. In addition, artificial intelligence technology is also applied in cutting-edge fields such as autonomous logistics fleets and drone delivery, providing more intelligent solutions for logistics transportation. Artificial intelligence can also help enterprises make more scientific decisions in complex supply chain environments through multi-party collaboration and big data analysis. By establishing an AI based decision support system, all parties can share information in real time, respond quickly to market changes, and ensure efficient collaboration in the supply chain.

Although the application of artificial intelligence in supply chain logistics has shown great potential, it still faces some challenges in practical operation, such as data quality and data sharing issues, interpretability of algorithm models, and organizational collaboration within enterprises.

2.3 Research gaps and development trends

Although significant progress has been made in the integration of artificial intelligence and supply chain management in existing research, there are still some research gaps and development trends that deserve further exploration [4].

The application of artificial intelligence in supply chain management faces multiple challenges, starting with issues of data quality and sharing. Due to the fact that data in the supply chain often comes from multiple heterogeneous systems, data integration and cleaning have become crucial, making it an urgent challenge to achieve cross system data sharing and integration while ensuring data quality. Secondly, the adaptability and interpretability of the algorithm also urgently need to be strengthened. Although AI algorithms have demonstrated excellent predictive and decision-making capabilities in many fields, the adaptability and interpretability issues of algorithms still exist in supply chain management, especially in decision-making scenarios where supply chain managers need to understand the decision-making process of the model to ensure that the results meet actual needs [5]. Therefore, developing AI algorithms with strong interpretability and good adaptability is a future research focus. Furthermore, real-time performance and dynamic optimization are the core requirements of modern supply chains. Traditional methods rely on historical data and regular updates, while modern supply chains require real-time response to market changes. How to improve the responsiveness of artificial intelligence technology in dealing with emergencies or severe market fluctuations is an urgent problem to be solved. In addition, cross departmental and cross enterprise collaboration is also an important challenge in supply chain management. How to achieve information sharing and decision-making collaboration between different organizations, improve overall response speed and decision-making efficiency, may rely on technologies such as blockchain as the future collaboration model. Finally, with the increasing awareness of environmental protection and the promotion of sustainable development goals, green supply chain management has gradually become a key direction for enterprise development. Combining artificial intelligence technology to achieve more environmentally friendly and efficient supply chain management will also be one of the research hotspots in the future.

3. AI-driven supply chain logistics prediction and optimization model

With the increasing complexity of supply chain management, the role of artificial intelligence in demand forecasting and decision optimization is becoming increasingly significant. Traditional supply chain management methods often rely on historical data and rule-based decision-making processes, while the introduction of artificial intelligence, especially in the fields of machine learning (ML) and deep learning (DL), has made prediction and optimization models more accurate and efficient.

3.1 Artificial intelligence methods for demand forecasting and decision optimization

Demand forecasting is one of the core issues in supply chain management. Accurate demand forecasting can effectively reduce inventory costs, improve service levels, and reduce fluctuations in production plans. Traditional demand forecasting methods mainly rely on statistical models (such as ARIMA, exponential smoothing, etc.), but these methods often cannot meet high-precision demand forecasting requirements when facing complex and dynamically changing market environments. Artificial intelligence methods, especially machine learning and deep learning methods, with their powerful data processing capabilities and adaptive learning characteristics, can significantly improve the accuracy of demand forecasting.

3.1.1 Machine learning based on demand forecasting method

Machine learning (ML) techniques, particularly regression models, support vector machines (SVM), random forests (RF), and gradient boosting trees (GBDT), have been widely used in demand forecasting. These methods can effectively capture non-linear patterns of demand changes through training on a large amount of historical data, thereby achieving more accurate demand forecasting. For example, the Random Forest (RF) algorithm is an ensemble learning method that makes predictions based on the voting results of multiple decision trees. Compared to traditional regression models, RF can effectively handle high-dimensional data and complex relationships between multiple variables. Therefore, in the face of complex market demand fluctuations, RF algorithms can provide more accurate prediction results.

3.1.2 Demand forecasting method based on deep learning

Deep learning (DL) models, especially long short-term memory (LSTM) networks and convolutional neural networks (CNN), have been widely used in time series prediction tasks. LSTM network, due to its powerful memory ability, can effectively capture long-term demand fluctuation patterns, making it particularly suitable for situations where demand has periodic fluctuations. In supply chain demand forecasting, LSTM models can not only predict future demand, but also provide real-time feedback on market changes, thereby providing more accurate support for supply chain management decisions.

3.1.3 Decision optimization methods

Artificial intelligence technology not only plays a role in demand forecasting, but also performs well in decision optimization. Reinforcement learning (RL) is an important decision optimization method in the field of artificial intelligence, which continuously adjusts strategies through interaction with the environment to achieve optimal decisions. In supply chain management, reinforcement learning can help companies optimize inventory management, transportation path selection, and production scheduling in complex multi-stage decision-making problems. For example, inventory management models based on reinforcement learning can adjust inventory levels according to real-time demand changes and supply chain status, minimizing stockouts or excess inventory, thereby reducing inventory costs and improving response speed.

3.2 Design and implementation of optimization model

3.2.1 Artificial intelligence models in supply chain optimization

Supply chain optimization problems typically involve multiple stages of decision-making, such as production, inventory management, transportation scheduling, and supplier selection. In this process, artificial intelligence models can continuously optimize the decision-making process through adaptive learning. For example, using deep reinforcement learning algorithms to optimize the decision-making process of multi-stage supply chains can effectively coordinate resource allocation between various links and maximize overall efficiency. Among them, deep reinforcement learning (DRL) models continuously adjust control strategies through interaction with the environment, achieving self optimization in the dynamically changing supply chain environment. This method is particularly suitable for use in dynamic environments, such as responding to emergencies, demand fluctuations, or supply chain disruptions.

3.2.2 Artificial intelligence model based on constraint optimization

In actual supply chains, optimization problems are often accompanied by multiple constraints, such as production capacity limitations, transportation costs, time constraints, etc. To cope with these constraints, artificial intelligence optimization models need to combine mathematical optimization methods such as linear programming (LP), integer programming (IP), and mixed integer programming (MIP), and combine them with machine learning algorithms to form a comprehensive optimization model. For example, combining heuristic algorithms such as genetic algorithm (GA) or ant colony algorithm (ACO) with constraint optimization can solve multi-objective and multi constraint supply chain optimization problems. Artificial intelligence methods can provide optimal or near optimal solutions by processing and simulating large amounts of data.

3.2.3 Implementation and application of optimization algorithms

The implementation of optimization algorithms typically relies on efficient computing platforms and algorithm design. The training of artificial intelligence models requires a large amount of data input and processing, so in practical applications, enterprises usually use cloud computing and high-performance computing platforms to achieve algorithm training and deployment. For example, inventory optimization models based on deep reinforcement learning can be trained using historical sales data, real-time inventory levels, supply chain delays, and other information to ultimately optimize inventory management strategies and reduce the occurrence of stockouts or excess inventory.

In order to verify the practical effectiveness of AI driven supply chain logistics prediction and optimization models, many enterprises and scholars have conducted a series of experiments and case studies. After applying an artificial intelligence demand forecasting model, a large retail enterprise successfully improved the accuracy of sales forecasting by adopting a time series forecasting model based on LSTM network. Before implementing artificial intelligence models, the company's traditional statistical methods often had significant prediction errors when facing seasonal fluctuations. After introducing LSTM, the model can accurately capture the cyclical changes in sales fluctuations, thereby helping enterprises make more precise inventory management decisions. The experimental results show that using the LSTM model reduces inventory costs by 15% and increases inventory turnover by 20%.

A manufacturing enterprise is facing production line capacity limitations and transportation delays. By using a reinforcement learning based production scheduling optimization model, it has successfully improved production efficiency and logistics scheduling response speed. By training reinforcement learning models, the enterprise is able to dynamically adjust production scheduling strategies based on real-time orders and supply chain status, achieving optimal utilization of the production line. The experimental results showed that production efficiency increased by 18% and transportation costs decreased by 12%. As shown in Table 1.

Table 1. Changes in inventory costs and inventory turnover before and after the implementation of the optimization model for retail enterprise demand forecasting

Time	Traditional methods of inventory cost	LSTM model inventory cost	Traditional methods of inventory turnover rate	LSTM model inventory turnover rate
Q1	¥200,000	¥170,000	4.5 times	5.4 times
Q2	¥210,000	¥180,000	4.2 times	5.2 times

From this Table 1, it can be seen that the use of LSTM model significantly reduces inventory costs and increases inventory turnover by nearly 20%. The application of artificial intelligence technology in supply chain logistics forecasting and optimization has significantly improved the accuracy of demand forecasting and the efficiency of decision optimization. Through methods such as machine learning, deep learning, and reinforcement learning, supply chain managers can more flexibly and accurately respond to complex and changing market demands and supply chain challenges. In the future, with further optimization of algorithms and development of computing platforms, AI driven supply chain optimization models will have greater potential in various industries.

4. Challenge and problem analysis

Although AI driven supply chain logistics prediction and optimization models have brought many benefits to enterprises, there are still many challenges and problems in practical applications. These challenges not only come from the technical and data aspects, but also involve ethical and security issues.

4.1 Technical and data challenges

In the supply chain optimization of artificial intelligence applications, data is the foundation for model training and decision-making. However, the data used in supply chain systems often comes from multiple different sources, such as suppliers, warehouses, retailers, and logistics service providers, and the quality and consistency of this data are often difficult to guarantee. Lack of standardized data structures, missing or erroneous data, and other issues may lead to a decline in the performance of artificial intelligence models, and even result in misleading decisions.

Data quality issues may have a significant impact on demand forecasting and inventory management, including data loss, data noise, and data standardization issues. Data loss can lead to models being unable to effectively learn and predict future trends, while data noise can reduce the accuracy of the model due to the interference of abnormal data or irrelevant variables, affecting the implementation effectiveness of optimization solutions. The problem of data standardization arises from inconsistent data formats from different sources, which increases the complexity of data integration and processing, thereby affecting the training and application effectiveness of the model. To solve these problems, data cleaning and preprocessing strategies can be adopted, and automated tools can be introduced to identify and repair errors and missing data to ensure data quality. At the same time, a unified data standard and protocol are adopted for data fusion and standardization to ensure effective integration of data from different sources, thereby improving the accuracy of prediction and optimization.

Artificial intelligence models, especially deep learning models, are often seen as "black box" models because their decision-making processes lack transparency. In supply chain optimization, the interpretability of the model is particularly crucial, especially when artificial intelligence makes decisions or predictions. Enterprises need to understand how the model produces these results in order to make reasonable adjustments or respond to potential risks. The problem of model interpretability mainly manifests as low decision transparency. If artificial intelligence cannot explain its decision basis, management may doubt the results, thereby affecting the trust of business operations; At the same time, tuning the model can become difficult because it is difficult to clearly understand how the model works. To address these issues, interpretable artificial intelligence (XAI) such as decision trees or LIME (Local Linear Models) can be employed, which can provide a more transparent decision-making process. In addition, combining manual analysis with artificial intelligence prediction results at critical decision-making moments can also help increase decision-making transparency and trust.

The training and application of artificial intelligence models usually require a large amount of computing resources and storage capacity, especially when dealing with complex supply chain problems. For large-scale supply chain systems, the amount of data and computation that artificial intelligence models need to process is often very large. Insufficient computing resources may lead to long model training times, making it difficult to make real-time optimization decisions, thereby affecting the efficiency of the supply chain. In addition, insufficient storage space may also become a bottleneck. As the amount of data increases, enterprises may face limitations in storage capacity, which in turn affects the efficiency of data access and processing. To solve these problems, cloud computing and edge computing can be used to share computing tasks on different platforms and devices, reduce resource bottlenecks, and improve the real-time performance of the model; In addition, introducing graphics processing units (GPUs) and specialized acceleration hardware (such as TPUs) can significantly improve the computational speed of model training and inference.

4.2 Ethical and safety issues

With the widespread application of artificial intelligence in supply chain systems, it involves a large amount of sensitive data, such as customer information, supplier contracts, and transaction records. Once these data are leaked or abused, it will have serious consequences on the reputation, customer trust, and legal compliance of the enterprise. Therefore, data privacy protection has become an important issue in artificial intelligence applications. Data breaches may lead to illegal access and leakage of private data of customers and suppliers, violating privacy rights, while artificial intelligence models may also cause privacy violations if they misuse data or collect sensitive information without knowledge. To address these issues, sensitive data can be protected through data encryption and anonymization, ensuring the security of the data during use, while strictly complying with relevant data protection laws and industry standards, such as applying the General Data Protection Regulation (GDPR) to ensure the legality of the data. However, with the popularization of artificial intelligence technology, the risk of malicious attacks cannot be ignored. For example, hackers may disrupt the decision-making process of artificial intelligence models by inputting malicious data, or cause system crashes or data tampering by attacking critical infrastructure in the supply chain. Therefore, security vulnerabilities in artificial intelligence systems may become potential hazards for supply chain disruptions, and security measures need to be strengthened to prevent malicious attacks.

Security issues pose significant risks to the application of artificial intelligence in the supply chain. Malicious attackers may manipulate the output of artificial intelligence models through adversarial samples, leading to erroneous decisions, and even causing system paralysis or data loss through distributed denial of service (DDoS) attacks and other means. To address these challenges, it is possible to strengthen the security of artificial intelligence, such as using adversarial training methods to enhance the robustness of AI models, improve their resistance to malicious attacks, and conduct regular security audits and real-time monitoring to detect and respond to potential security threats in a timely manner. However, the application of artificial intelligence may also raise ethical issues, especially in the supply chain, where AI may lead to unemployment risks, especially when automation is too high. In addition, artificial intelligence decision-making may sometimes lack attention to human factors, neglect social responsibility and environmental impact, so these ethical issues need to be comprehensively considered when applied.

The impact of ethical issues in the application of artificial intelligence cannot be ignored, as large-scale automation may replace traditional jobs, leading to unemployment risks and social instability. Meanwhile, if artificial intelligence models fail to fairly and justly process data from different groups, it may lead to algorithmic bias, resulting in unfair decision-making and even exacerbating social inequality. To address these issues, solutions include conducting ethical review and compliance when designing and applying artificial intelligence systems, ensuring full consideration of social responsibility and ethical norms, and avoiding algorithmic bias. In addition, artificial intelligence should collaborate with humans rather than simply replace them, emphasizing the cooperation between AI and human employees to ensure that technological progress can create dual benefits for society and the economy.

5. Conclusion

This study focuses on supply chain logistics prediction and decision optimization driven by artificial intelligence, analyzing the potential application of artificial intelligence technology in the supply chain and the changes it brings. Through exploring the application of artificial intelligence technologies such as machine learning and deep learning in logistics prediction and decision optimization, research has shown that artificial intelligence can significantly improve supply chain efficiency, enhance prediction accuracy, reduce inventory costs, optimize transportation routes, and accelerate response speed, providing enterprises with more competitive advantages.

However, the widespread application of artificial intelligence in supply chain logistics still faces certain challenges, especially in terms of data quality, model reliability, and algorithm transparency. In order to ensure the smooth application of artificial intelligence technology, enterprises need to strengthen data collection and management to ensure the accuracy and completeness of data. At the same time, promoting the interpretability research of artificial intelligence models, improving the transparency of decision-making, and enhancing the trust of management in the results of artificial intelligence decisions. In the future, with the continuous advancement of technology, artificial intelligence will play an increasingly important role in the field of supply chain logistics. In order to maximize its application value, it is recommended to strengthen interdisciplinary cooperation, continuously optimize algorithms based on industry needs, and develop compliant ethical frameworks to ensure that technology applications comply with social responsibility and ethical norms.

In short, artificial intelligence provides unprecedented opportunities for prediction and decision optimization in supply chain logistics, while also requiring us to face the challenges in technological applications with a more pragmatic and responsible attitude. Through continuous innovation and adjustment, artificial intelligence will drive supply chain logistics towards a more efficient and intelligent era in the future.

ISSN 2616-5902 Vol. 7, Issue 2: 132-139, DOI: 10.25236/AJBM.2025.070218

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