INTI JOURNAL | Vol.2025, Issue 5, No.4
eISSN:2600-7320

Artificial Intelligence Empowers Sustainable Supply Chains

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Abstract

With the continuous turbulence in the global market and the rapid development of artificial intelligence (AI), the sustainable development of supply chains has attracted significant attention. Addressing the "efficiency-environmental protection-equity" challenges faced by current sustainable supply chains, this paper attempts to analyze how AI can empower sustainable supply chains and explores AI's ability to handle the dynamic complexity of supply chains, including real-time data monitoring, accurate prediction, intelligent decision-making, risk management, data sharing, and continuous learning. The study finds that AI can empower sustainable supply chains through the following aspects: demand forecasting and inventory optimization, logistics network optimization, supply chain risk management, supplier management, production and manufacturing optimization, real-time monitoring and transparency, as well as carbon footprint management and emission reduction optimization. Through these means, AI helps improve supply chain efficiency, reduce costs, enhance forecasting and demand management capabilities, strengthen risk management and emergency response capabilities, and boost supply chain resilience.

Keywords

Artificial intelligence empowerment; Sustainable supply chains; Low-carbon emission reduction

Introduction

With the rapid development of global industry and economy, supply chains have witnessed tremendous growth, playing a crucial role in global economic trade and creating substantial profits for enterprises. However, environmental pollution has become increasingly prominent. In response, the United Nations and various countries have introduced relevant policies, proposing sustainable development strategies and corresponding measures.

In 2024, China's State Council issued the 2024-2025 Energy Conservation and Carbon Emission Reduction Action Plan, clearly defining carbon emission targets for 2024-2025. It requires a reduction of approximately 3.9% in carbon dioxide emissions by 2024 and about 130 million tons by 2025, striving to achieve the binding energy conservation and carbon reduction targets of the 14th Five-Year Plan. According to the International Energy Agency (IEA, 2025), global energy-related carbon emissions increased by 0.8% in 2024, slowing

Submission: 14 August 2025; **Acceptance:** 20 November 2025; **Available online:** November 2025

down from the 1.1% growth in 2023 and 1.4% in 2022. Notably, China's total carbon emissions remained at 12.6 billion tons in 2024, the same as in 2023, achieving zero growth, indicating the initial effectiveness of energy conservation and carbon reduction efforts. However, compared with the action plan, the task of energy conservation and emission reduction remains arduous. Moreover, global carbon emissions reached 37.8 billion tons in 2024, a historical high, highlighting that carbon emissions remain a critical issue in sustainable development.

The 2024 Government Work Report emphasizes "vigorously developing green and low-carbon economy" and "promoting the research, development, and application of advanced energy conservation and carbon reduction technologies to accelerate the formation of green and low-carbon supply chains (Li, 2024) reflecting the Chinese government's high attention to green development and sustainable development. This also provides a clear direction and action guide for promoting high-quality economic development and achieving the goals of carbon peak and carbon neutrality. Against this backdrop, the green and low-carbon economy has become a new trend in global economic development, and the sustainable development of global supply chains face enormous challenges (Li, 2024).

With the continuous turbulence of the global market and the accelerated development of technological innovation, supply chain managers are confronted with unprecedented challenges. According to the 2025 Supply Chain Trends Report released by ASCM (2025), artificial intelligence (AI) is ranked first—this is not only the result of technological development, but also a reflection of the market's urgent demand for intelligent decision support.

By adopting the literature research method, this paper sorts out the application of sustainable development theory in supply chains and the rise of artificial intelligence (AI). It also attempts to analyze how AI can empower sustainable supply chains in the digital and intelligent era, as well as how to improve efficiency and supply chain resilience while taking environmental protection into account.

Methodology

By means of the total number of literature methods, this chapter expounds on sustainable development supply chains, artificial intelligence (AI) technology, and AI's ability to handle the dynamic complexity of supply chains.

Concept of Sustainable Development Supply Chain

The concept of sustainable development can be traced back to the World Conservation Strategy in the 1980s. The 1987 report Our Common Future by the World Commission on Environment and Development first proposed the concept of sustainable development, defining sustainability as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs", referring to the capability to maintain a process or state at a specific lasting level. In 1998, British scholar Elkington first proposed the Triple Bottom Line (TBL) theory, which reflects the connotation of sustainable development, and deeply explored the three dimensions of economy, society, and environment included in sustainability (Elkington, 1998). Subsequently, Carter and Rogers applied the sustainable development theory to supply chains, defining sustainable supply chain management as a strategic and transparent integration to achieve social, environmental, and economic goals (Carter & Rogers, 2008).

Currently, the definition of sustainable supply chains by Seuring and Muller is widely accepted. A sustainable supply chain achieves coordinated development of economy, environment, and society through the management of logistics, information flow, and capital flow, as well as collaboration among chain members (Seuring & Müller, 2008). Song Hua pointed out that the supply chain has entered the 5.0 stage, which is based on artificial intelligence. He defined the AI-powered smart supply chain as "a comprehensive integrated technology and management system that achieves intelligence, networking, collaboration, integration, and automation based on artificial intelligence and machine learning." Through human-machine collaboration and integration, the AI-powered smart supply chain is becoming an autonomous supply chain with characteristics such as self-awareness, self-determination, and self-optimization, and its industrial development goals are resilient and sustainable (Song, 2024).

Artificial Intelligence Technology

The term "artificial intelligence" can be traced back to the 1950s, initially intending to explore the ability of machines to use language to solve problems reserved for humans (McCarthy et al., 2006). This proposal marked the formal birth of AI as an emerging discipline. After more than 40 years of development, artificial intelligence has become an interdisciplinary and cutting-edge science (Liu, 2004). However, scholars from different fields and disciplines define it differently. Cai Zixing defined artificial intelligence as intelligent machines that can autonomously or interactively perform various human-like tasks in various environments. Their execution functions are usually related to human intelligence, such as judgment, reasoning, proof, recognition, perception, understanding, design, thinking, planning, learning, and problem-solving (Cai & Xu, 1996).

In recent years, the academic community has gradually reached a consensus on the connotation of artificial intelligence, believing that it is a machine system that can communicate with humans, imitate humans, and enhance human cognition. It can provide suggestions for planning, evaluation, prediction, or solving business problems, and even handle problems that humans cannot solve (Riahi et al., 2021; McCarthy et al., 2006; Huang et al., 2018). Mike (2024), the supply chain consulting director of IBM, pointed out in *ASCM's Top 10 Supply Chain Trends for 2024*: "AI is not here to replace human decision-making, but to enhance human decision-making capabilities by providing more intelligent information support". Combining multiple technologies such as machine learning and cognitive computing, artificial intelligence can achieve or even exceed human intelligence levels within a certain range (Chen, 2023). In dealing with different emergency management, artificial intelligence needs to be based on fundamental and technical levels and consider the common characteristics of solution logic (Zhou et al., 2020). Algorithms are the core driving factor for the development of artificial intelligence, with machine learning as its core (Luo et al., 2023).

Artificial intelligence is the most dynamic general-purpose technology in the Fourth Industrial Revolution. It supports the new industrialization through four dimensions: production factors, platform organization, industrial transformation and upgrading, and deep integration of digital and real economies, with "innovation chain + value chain" as the basic support, "innovation chain + supply chain" as the key support, "innovation chain + industrial chain" as the core support, and "innovation chain + ecological chain" as the important support（Shu et al. , 2025).

Artificial intelligence has advantages such as self-innovation, cross-border integration,

and efficient operation, which help promote green technological innovation and accelerate the transformation of traditional industries towards intensification and greening, thus laying a foundation for accelerating the low-carbon economic transition (Zhang, 2025). The underlying technical logic of artificial intelligence has always been data collection, analysis, and modeling. It can optimize the labor structure through substitution effects, greenify production methods through technical effects, and achieve intelligent management through intelligent monitoring and analysis, thereby promoting collaborative governance of pollution reduction and carbon emission reduction (Zhang, 2025).

AI's Capability to Handle Dynamic Complexity of Supply Chains

The "intelligence" of artificial intelligence lies in its strategies, and its advantages are reflected in efficiently processing complex information in supply chains and providing decision support for supply chain production, transportation, distribution, and information collaboration. AI demonstrates significant advantages in handling the dynamic complexity of supply chains, with its core capabilities embodied in dimensions such as real-time data processing, multi-variable prediction, intelligent decision optimization, and risk adaptive response.

Real-time data monitoring and dynamic processing: The complexity of supply chains mainly stems from numerous nodes, multiple links, and cross-connections, involving multiple dimensions such as logistics, inventory, production, and demand data. AI can use IoT, RFID, sensors, and big data technologies to collect, integrate, and analyze dynamic data from all links in the supply chain in real time. For example, in warehouse management, AI can use RFID, computing, and other technologies to monitor inventory levels, cargo transportation, order replenishment, etc., in real time, identify data anomalies, issue warnings, and avoid potential problems such as inventory shortages and transportation delays. This real-time monitoring capability enables enterprises to quickly respond to dynamic changes in the supply chain, reduce disruption risks, and improve supply chain resilience.

Intelligent decision-making and automation: Decision-making in supply chains often involves multi-objective optimization, such as efficiency, cost, service level, sustainability, and supply chain resilience, and requires quick decisions under uncertain conditions. AI can use technologies such as reinforcement learning and optimization algorithms to simulate different decision scenarios and determine the best solution. For example, in logistics route scheduling, AI can optimize transportation routes based on real-time environments to balance transportation costs and final delivery time, thereby improving service levels.

Risk management and resilient supply chain realization: External environmental risks, such as political conflicts, economic trade wars, Sudden occurrence pandemics, natural disasters, and supplier bankruptcies, are also causes of supply chain dynamic complexity. On the one hand, AI can analyze suppliers' geographical locations, production capabilities, and financial health to identify potential risks in advance, adjust procurement decisions in a timely manner, or recommend alternative suppliers in advance. On the other hand, AI can simulate supply chain disruption scenarios through digital twin technology to help enterprises test and optimize resilience strategies.

Supply chain collaboration and transparency: Information asymmetry among nodes or participants easily leads to insufficient overall supply chain collaboration and exacerbates supply chain complexity. AI can use technologies such as blockchain and cloud computing to achieve supply chain data sharing and transparency, thereby promoting collaboration among all nodes and links. For example, an AI-driven supply chain management platform can

synchronize real-time order status, inventory levels, and production progress, reducing information delays and communication costs.

Continuous learning and adaptation: The dynamic environment of the supply chain requires the system to have continuous learning and adaptive capabilities. Through machine learning algorithms, AI can continuously learn from new data and optimize model performance. For example, AI can automatically adjust the parameters of the prediction model based on the deviation between actual demand and prediction to achieve accurate forecasting. Meanwhile, AI's adaptive capabilities can cope with long-term changes (such as market demand evolution, technological progress) and short-term fluctuations in the supply chain.

Results and Discussion

Artificial intelligence (AI) empowers sustainable supply chains through demand forecasting and inventory optimization, logistics network optimization, supply chain risk management, supplier management, production manufacturing optimization, etc., specifically reflected in the following aspects:

Demand Forecasting and Inventory Optimization

AI analyzes massive data such as historical sales data, market trends, consumer behavior, weather information, and social media public opinion, and automatically adjusts the parameters of the forecasting model based on data conditions to achieve more accurate demand forecasting. This helps enterprises optimize inventory levels, reduce inventory backlogs and stockouts, thereby minimizing resource waste and costs. For example, retail enterprises can predict best-selling products in advance, rationally arrange production bases, adjust production plans, and shorten delivery cycles.

Logistics Network Optimization

In the logistics link, AI can analyze transportation status in real time, estimate port congestion levels, and plan optimal transportation routes and international logistics solutions in advance by integrating real-time traffic and customs data, reducing transportation costs and carbon emissions. For instance, dynamic adjustment of transportation paths can minimize fuel consumption and delivery time.

Supply Chain Risk Management、Supplier Management and Production Manufacturing Optimization

AI continuously analyzes and monitors data to identify potential threats and provides advanced risk management solutions. By monitoring global risk factors such as natural disasters and political instability, enterprises can adjust procurement plans in advance to reduce the risk of supply chain disruption.

By using AI to analyze supplier delivery efficiency, risk factors, integrity, and compliance, enterprises can optimize supplier selection, enhance supplier reliability, mitigate supply chain risks, and reduce procurement costs. For example, evaluating suppliers' energy consumption and resource use enables enterprises to choose more environmentally friendly suppliers.

AI can integrate real-time data on order demand, equipment status, and raw material inventory to dynamically adjust production plans, achieve demand-driven production, reduce

inventory shortages and understocking, and avoid production capacity waste. For instance, predicting equipment failures in advance allows scheduled maintenance, reducing downtime and extending equipment life.

Real-time Monitoring and Transparency

AI integrates multi-source data to monitor goods status and location in real time, providing end-to-end supply chain transparency. For example, through IoT sensors and AI algorithms, enterprises can track goods transportation in real time to ensure safety and reduce losses.

Carbon Footprint Management and Emission Reduction Optimization

Using technologies such as machine learning, blockchain, and data fusion, AI calculates product carbon footprints based on enterprise data, models and analyzes supply chain emissions, and identifies cost-optimal emission reduction opportunities. Enterprises can efficiently inventory their carbon footprints, identify and control emissions from the source, quantify the impact of decisions on procurement, transportation, and warehousing on carbon emissions, and optimize configurations.

Conclusion

The study finds that AI has the ability to handle the dynamic complexity of supply chains, including real-time data monitoring, demand forecasting, intelligent decision-making, risk management, data sharing and transparency, continuous learning, etc. When AI empowers sustainable supply chains, it is specifically reflected in the following aspects: demand forecasting and inventory optimization, logistics network optimization, supply chain risk management, supplier management, production manufacturing optimization, real-time monitoring and transparency, carbon footprint management and emission reduction optimization.

Acknowledgements

This work was supported by The Second Batch of University-Level Digital and Intelligent Demonstration Courses of Southwest Jiaotong University Hope College (Project No.: SZH2025006)

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