

Pathways for AI-Driven Green and Low-Carbon Transition of Supply Chains

Jinkai Ke

China National Tendering Center of Mach. & Elec. Equipment (Government Procurement Center of MIIT), Beijing, China
Email: kejinkai@miitcntc.org.cn

How to cite this paper: Ke, J. K. (2026). Pathways for AI-Driven Green and Low-Carbon Transition of Supply Chains. *Modern Economy*, 17, 860-868.
<https://doi.org/10.4236/me.2026.176044>

Received: March 27, 2026

Accepted: June 27, 2026

Published: June 30, 2026

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Abstract

Global supply chains account for approximately 60% of total carbon emissions worldwide, yet fragmented information across multiple actors and divergent interest objectives render systemic emission reductions unattainable through traditional management approaches. This paper delineates four pathways through which artificial intelligence (AI) drives the green and low-carbon transition of supply chains: intelligent demand sensing enhances supply-demand matching, curbing superfluous emissions at the source; intelligent logistics scheduling optimizes the trade-off among cost, delivery time, and energy consumption; chain-wide carbon footprint traceability addresses Scope 3 emissions; and supplier collaboration and empowerment promote green and low-carbon transformation. It also identifies structural limitations inherent in these pathways, including fragmented data governance, the opacity of algorithmic decision-making rationales, organizational incentive misalignments, and environmental rebound risks arising from the computing power consumption of AI itself. Accordingly, the paper proposes optimization directions such as constructing a cross-organizational carbon data governance framework, developing explainable carbon decision intelligence models, designing collaborative carbon-reduction incentive mechanisms that balance equity and efficiency, and establishing a full-life-cycle carbon performance evaluation system. Embedding institutional design into technical processes enables AI to evolve from an efficiency tool into an institutional infrastructure for the green governance of supply chains.

Keywords

Artificial Intelligence, Green and Low-Carbon Supply Chain, Pathway Optimization

1. Introduction

Research jointly conducted by the World Bank's Climate Investment Funds and

CDP on large multinational enterprises indicates that Scope 3 carbon emissions from supply chains in sectors such as energy, industry, transportation, and consumer goods account for approximately 60% of total global carbon emissions, spanning raw material extraction, manufacturing and processing, logistics and transportation, consumption, and end-of-life disposal and recycling (Yang et al., 2025). Because supply chains involve multiple decision-making entities and carbon emissions are mutually embedded across nodes with blurred boundaries, traditional environmental management approaches struggle to achieve systemic emission reductions. This predicament stems from fragmented and opaque information among actors, which makes it difficult to accurately identify the sources of energy consumption and carbon emissions (Kumar et al., 2023). Moreover, the misaligned interest objectives of different actors lead to an uneven distribution of abatement costs and benefits, further weakening the willingness to engage in collective action (Srivastava, 2007).

AI offers technical possibilities for resolving these contradictions by enhancing green technology innovation and optimizing logistics decisions, among other emission-reduction levers. However, existing research emphasizes application scenarios while overlooking pathway logic, and focuses on technical realization while neglecting institutional challenges such as organizational governance (Nureen et al., 2023). Therefore, this paper systematically examines the pathways through which AI drives the green and low-carbon transition of supply chains, analyzes the limitations of each pathway in turn, and proposes corresponding optimization directions. This paper conducts a systematic analysis based on practical cases. By reviewing recent academic literature on the application of AI to the green, low-carbon, and sustainable development of supply chains, relevant industry analysis cases, and specific application scenarios where AI empowers industries, and by analyzing related industry policies, the potential pathways through which AI drives the green and low-carbon transition of supply chains are identified. These pathways are organized according to carbon management objectives source reduction, operational efficiency, emission traceability, and network collaboration forming the major functional domains of supply chain management to which they correspond.

In this study, AI-driven is defined as the use of AI technologies to optimize and enhance supply chain decision making and operational processes. The green and low-carbon transition of supply chains refers to a systemic shift in supply chain operations toward an environmentally sustainable model with reduced greenhouse gas emissions. Pathway, in the context of this paper, specifically denotes a distinctive means or approach by which AI technologies drive specific carbon reduction objectives within supply chains.

2. Existing Pathways for the AI-Driven Green and Low-Carbon Transition of Supply Chains

The pathways delineated in this section are categorized according to carbon man-

agement objectives. The first pathway, intelligent forecasting for supply-demand matching, focuses on source reduction; the second, energy-efficiency optimization through intelligent logistics scheduling, focuses on operational efficiency; the third, chain-wide carbon footprint management for traceability, focuses on emission traceability; and the fourth, supplier collaboration and empowerment for green development, focuses on network collaboration. Together, these four pathways cover the primary functional domains in which AI applications are currently concentrated, including demand planning, logistics operations, carbon accounting, and supplier governance.

2.1. The Supply-Demand Matching Pathway Enabled by Intelligent Forecasting

Supply-demand mismatches constitute a major source of overproduction, inventory redundancy, and reverse logistics for returns, generating unnecessary emissions in procurement, manufacturing, and logistics (Feng, Lai, & Zhu, 2022). Traditional forecasting relies heavily on linear extrapolation of historical sales data and is poorly equipped to perceive abrupt shifts in consumer demand. By integrating multi-source data-such as historical sales records, social media sentiment, meteorological information, and macroeconomic indicators-AI constructs demand sensing models that transmit front-end consumption signals backward to manufacturing and procurement. This enables enterprises to implement demand-driven purchasing, demand-driven production scheduling, and dynamic regional inventory allocation, thereby reducing uncertainty and conserving resource inputs at the source (Sheng et al., 2023). Taking JD Logistics' effective case practice as an example, its self-developed MRV-T (Monitoring, Reporting, Verification, and Tracking) system links demand signals arising from order fluctuations with various carbon emission factor datasets, uses AI models to analyze energy consumption in real time, and dynamically adjusts capacity allocation, thereby promoting end-to-end supply-demand matching.

2.2. The Energy-Efficiency Optimization Pathway through Intelligent Logistics Scheduling

Logistics and transportation represent the most visible and proportionally significant carbon-emitting segment of supply chains. Traditional scheduling often takes the shortest distance or the lowest cost as a single objective, making it difficult to incorporate energy and carbon constraints (Khan et al., 2023). By introducing real-time traffic, weather, time-of-use electricity tariffs, and other multi-dimensional variables, and by simulating warehouse node location choices and multi-modal transport combinations, AI can support more balanced decision making among transportation cost, delivery time, energy consumption, and carbon emissions. As an illustration, Schneider Electric decomposes its emission reduction targets into a set of executable measures and employs AI models for intelligent scheduling, optimizing substantial reductions in both transportation costs and energy- and carbon-related consumption.

2.3. The Traceability Pathway through Chain-Wide Carbon Footprint Management

A prerequisite for the green and low-carbon transition of supply chains is the traceability of emission sources. Traditional accounting methods rely on industry-average emission factors and cannot support precise, batch-by-batch or node-by-node decision-making. This is especially true for Scope 3 emissions, which account for the overwhelming majority of a firm's carbon footprint. Because supplier tiers are numerous, data remain persistently opaque, rendering most emissions effectively untraceable (Yan et al., 2026). AI is beginning to break this deadlock. By leveraging technologies such as natural language processing and computer vision, it can automatically extract and parse energy consumption and carbon emission data from unstructured information such as suppliers' environmental compliance reports and transportation energy records, thereby helping to dismantle information barriers inside and outside enterprise boundaries and laying a foundation for accurately defining carbon footprint management responsibilities.

2.4. The Green Development Pathway through Supplier Collaboration and Empowerment

The green transition of a supply chain cannot be accomplished by a single focal firm alone; its effectiveness depends to a large degree on the collective response of the supplier network. The critical challenges lie in effectively identifying green performers among a vast number of suppliers and in incentivizing and empowering numerous small and medium-sized enterprises to invest in energy saving and carbon reduction (Lerman et al., 2022). Using industrial knowledge graphs and multi-dimensional machine learning, AI can construct supplier evaluation models that integrate indicators such as energy intensity, carbon footprint management maturity, and the share of renewable energy, thereby giving green preference in procurement sourcing and tendering. Taking Alibaba Cloud's "Energy Expert" (Nenghaobao) as an illustrative case of an AI-based sustainability tool, this tool can automatically calculate carbon emissions for organizations, including small and medium-sized suppliers, and provide optimization recommendations, thereby supporting the green and low-carbon coordinated development of the supply chain network.

3. Structural Limitations of the Existing Pathways

Although the pathways outlined above demonstrate AI's energy-saving and carbon-reduction potential across different dimensions, they remain subject to structural limitations.

3.1. Fragmentation of Data Governance

The existing pathways are highly dependent on the supply of high-quality, standardized data, which is precisely the scarcest resource in supply chains. Current

levels of enterprise digitalization are uneven, and inconsistencies in data formats, accounting scopes, and boundary definitions create intrinsic deficiencies in model training data. Scope 3 carbon emissions involve multi-tier suppliers; the further upstream one goes, the lower the availability and reliability of data become (Wired et al., 2024). A large number of small and medium-sized enterprises have yet to adopt automated data management systems, thereby constraining the analytical precision of models.

3.2. The Credibility Dilemma of Algorithmic Decision-Making

The application of AI in carbon management is transitioning from descriptive analysis to prescriptive decision-making, yet the internal reasoning processes of some deep learning models remain highly opaque to managers. When models output green, energy-saving, and carbon-reduction recommendations in a “black-box” manner, decision-makers tend to be cautious. This contradiction is particularly pronounced in the carbon emissions domain: carbon data are already subject to considerable uncertainty, and when this is compounded by the uninterpretability of algorithmic reasoning, managers’ willingness to adopt model outputs is doubly suppressed.

3.3. Organizational Incentive Misalignment

The green transition of supply chains faces a classic collective action dilemma: investments in energy saving and carbon reduction are concentrated in focal lead firms or first-tier suppliers, whereas the benefits are dispersed across the entire supply chain and society at large (Lerman et al., 2022). The introduction of AI not only fails to automatically resolve this dilemma but may actually exacerbate incentive misalignments. Focal lead firms possess advantages in capital, data, and talent for deploying energy and carbon management systems, while the vast majority of small and medium-sized suppliers lack both technical capability and the prospect of recouping the costs of green retrofitting within short-term commercial returns. In fragmented supply chain structures that lack a dominant focal firm, the transaction costs of collaborative emission reduction will continue to rise.

3.4. Environmental Rebound Risks

AI technology itself is not carbon-neutral. Large language models consume substantial computing power during both training and inference phases; embedding them into supply chain management systems inevitably incurs additional energy consumption. Locally achieved emission reductions driven by AI may, at the system level, be partially or even fully offset by the technology’s own carbon footprint, producing a rebound effect. If this additional emission burden is not incorporated into the overall carbon accounting framework of the supply chain, the net environmental contribution of AI-driven carbon reduction cannot be accurately measured. The high energy consumption of certain models, together with limited

data interoperability and insufficient scalability, constitute major obstacles to the current technological pathways. In the absence of a full-life-cycle carbon performance evaluation mechanism, the effectiveness of the AI-driven green and low-carbon transition of supply chains will be exposed to rebound risks.

4. Analysis of Pathway Optimization

Identifying the above limitations provides clear directions for optimizing the pathways for the AI-driven green and low-carbon transition of supply chains.

4.1. Constructing a Cross-Organizational Carbon Data Governance Framework

The key to overcoming data fragmentation lies in institutional arrangements. Promoting the standardization of carbon emission data enables AI models to support data interoperability across different supply chain contexts, thereby laying a foundation for large-scale application. By adopting privacy-preserving computation techniques such as secure multi-party computation, data ownership can be empowered and collaborative modeling can be realized, protecting the commercial secrets of all parties while guaranteeing coordinated green development for energy conservation and carbon reduction. Simultaneously, cloud-based deployment and lightweight tools can lower the access threshold for small and medium-sized enterprises, preventing technological barriers from creating a new green digital divide.

4.2. Developing Explainable Carbon Decision Intelligence Models

To address the algorithmic credibility dilemma, explainability should be established as a rigid constraint in model design. In terms of methodological choices, structurally transparent approaches such as decision trees, rule learning, and explainable boosting tree models should be prioritized for identifying key carbon emission factors and generating strategies. For scenarios that necessitate high-precision complex models, post-hoc explanation techniques should be supplemented, so that every emission-reduction recommendation is accompanied by a traceable reasoning rationale. By deeply coupling the algorithmic output logic with existing supply chain management processes such as audit trails, exception reviews, and compliance approvals each emission-reduction recommendation carries an interpretable business rule explanation. Only then can AI be transformed from an auxiliary technical tool into a trusted decision-making partner for managers, thereby genuinely mitigating the negative resistance and skepticism arising from “black-box” decisions.

4.3. Designing Collaborative Carbon-Reduction Incentive Mechanisms That Balance Equity and Efficiency

Resolving incentive misalignments requires internalizing the externalities of energy saving, emission reduction, and carbon mitigation through institutional de-

sign and intelligent execution. Focal lead firms can leverage the real-time performance tracking capabilities of AI to offer tiered incentive schemes such as preferential procurement quotas, priority purchasing, or favorable payment terms to suppliers that consistently improve their energy and carbon performance, thereby directly converting emission-reduction behavior into tangible economic returns. In the future, smart contracts can be introduced to upload verified emission-reduction performance from each node onto a blockchain for immutable record-keeping, automatically executing carbon credit transfers or financial compensation according to pre-defined rules. This decentralized automatic settlement can substantially reduce the transaction costs of multi-party verification and repeated negotiation, while also rendering the relationship between emission-reduction contributions and corresponding rewards transparent and clear, thus effectively curbing free-riding behavior. In this way, the efficiency gains generated by technology and the equity pursued by institutions reinforce each other, forming a synergistic development pattern that is complementary rather than conflicting.

4.4. Establishing a Full-Life-Cycle Carbon Performance Evaluation Mechanism

To guard against rebound risks, the carbon footprint of the AI system itself must be incorporated within the accounting boundary. During the system planning stage, energy and carbon consumption evaluation indicators should be introduced; lightweight models and green data centers should be prioritized to contain the technology's carbon cost at the source. A scientifically rigorous accounting methodology should be constructed, deducting the carbon cost of model training and inference from the driven emission reductions and using the net contribution as the ultimate yardstick of effectiveness. Taking a full-life-cycle perspective to calculate the net contribution of the baseline prevents local optimizations from imposing new environmental costs at the system boundary, thereby ensuring that AI technology achieves a net reduction in energy and carbon, rather than engaging in a covert transfer of carbon burden between computing resources and the supply chain.

5. Conclusion

The relationship between AI and the green and low-carbon transition of supply chains is, in essence, a question of how technological rationality and collective rationality mutually construct one another. Technology can provide more precise carbon emission sensing and more efficient optimization algorithms, yet it cannot automatically dissolve interest divergences among actors.

The analysis in this paper demonstrates that embedding institutional design into technical processes, and achieving mutual adaptation between algorithmic logic and governance logic, optimizes the pathways for the AI-driven green and low-carbon transition of supply chains. Specifically, this involves breaking down information silos through cross-organizational data governance, building trust

through explainable decision-making logic, converting emission-reduction behavior into predictable economic returns through incentive-compatible mechanisms that balance equity, and preventing the computing power consumption of the technology itself from offsetting energy-saving and carbon-reduction benefits through full-life-cycle carbon performance evaluation.

Future research should continue to advance along the directions of consolidating the data foundation, enhancing algorithmic trustworthiness, achieving incentive compatibility, and perfecting the evaluation feedback loop. Key breakthroughs should focus on the technological integration of privacy-preserving computation and carbon footprint traceability, the institutional embedding of explainable AI within supply chain auditing, and decentralized carbon credit settlement mechanisms driven by smart contracts, so that AI evolves from an efficiency tool into an institutional infrastructure for the green governance of supply chains.

Acknowledgements

Thanks to the Soft Science Research Project “Research on Government Procurement Promoting the Innovative Development of the Environmental Protection Equipment Industry” of China National Tendering Center of Mach. & Elec. Equipment (Government Procurement Center of MIIT).

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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