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AI-DRIVEN ROUTE OPTIMIZATION FOR GREEN AND EFFICIENT GLOBAL VALUE CHAINS

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Abstract: The rapid growth of global supply chains has brought major environmental challenges, particularly through rising transport-related emissions. In response, businesses and policymakers increasingly view artificial intelligence (AI) as a tool for achieving both operational efficiency and sustainability. This paper analyses the potential of AI-driven route optimisation within the context of green supply chains. The theoretical framework contrasts AI with classical optimisation methods, highlighting how machine learning, heuristics, and reinforcement learning introduce adaptability, scalability, and multi-objective optimisation that traditional models lack. The empirical part reviews three areas of AI application. Transport and logistics illustrate direct contributions through route optimisation, last mile efficiency, and multimodal planning. Predictive analytics improves demand forecasting and risk anticipation, reducing unnecessary trips and inventories. Digital twins and simulation offer advanced modelling for complex logistics systems, supporting resilience and sustainability under uncertainty. Practical illustrations demonstrate the tangible impact of these technologies. The paper concludes that AI-driven optimisation is not merely a technical innovation but a structural enabler of the green transition, aligning operational efficiency with sustainability objectives and paving the way for more resilient global value chains.

Keywords: *Artificial Intelligence, Route Optimisation, Green Transition, Global Value Chains, Sustainable Logistics, Digitalisation.*

INTRODUCTION

The rapid expansion of global supply chains has transformed trade and industry but has also intensified environmental pressures through higher carbon emissions, resource use, and ecological degradation. Freight transport alone accounts for a large share of global greenhouse gas emissions, and these figures continue to rise with the growing demand generated by e-commerce, urbanisation, and international trade (Jahagirdar, 2025). This has prompted both businesses and governments to search for sustainable logistics solutions. Artificial intelligence represents one of the most promising tools in this transition, offering new ways to optimise logistics, reduce carbon footprints, and build greener and more resilient supply chain networks.

The notion of the green supply chain was first introduced in the 1990s as a management model that integrates environmental protection, efficient resource use, and economic benefits across all supply chain stages. It emphasises aligning upstream and downstream relationships to incorporate principles of low-carbon technologies and energy conservation into production, logistics, and recycling processes. The ultimate aim is to enhance profitability while minimising environmental impacts (McKinnon et al., 2015; Xie, 2025; Ghaderi et al., 2023).

Global supply chains are therefore both a major source of emissions and a critical lever for the green transition. Their scale and complexity make them highly resource-intensive, but at the same time they provide opportunities for significant reductions in carbon footprints if supported by digitalisation and AI-based optimisation. Digital technologies enable the collection and processing of vast datasets, while AI introduces the ability to identify patterns, anticipate risks, and support real-time decision-making across logistics systems.

The aim of this paper is to analyse the potential of AI for route optimisation with a particular focus on sustainability. The contribution lies in linking AI-driven methods not only to operational efficiency but also to the broader objectives of reducing emissions, lowering resource consumption, and building greener supply networks.

The paper is structured into three main parts. The first, *Theoretical Framework: AI and Route Optimisation*, outlines the fundamental concepts of machine learning, contrasts AI with classical optimisation approaches, and highlights the environmental dimension of AI-based decision-making. The second, *Applications of AI in Green Supply Chains*, examines how AI is applied in transport and logistics, predictive analytics, and digital twin technologies to improve sustainability. The third, *Discussion and Conclusions*, reflects on the main findings, identifies limitations, and considers the wider implications for green transition policies and digital transformation.

Despite the growing body of research on AI in supply chains, most studies tend to focus on either operational efficiency or broad sustainability goals, often without linking the two in a systematic manner. This paper seeks to address this gap by analysing how AI-driven methods can simultaneously improve logistics efficiency and advance sustainability objectives. In doing so, it contributes to the literature by bridging theoretical insights with practical illustrations and by outlining directions for further research on the role of AI in building greener and more resilient supply chains.

1. Theoretical Framework: AI and Route Optimisation

1.1. Fundamental Concepts: Machine Learning, Heuristics, and Reinforcement Learning

Artificial intelligence in logistics is most often applied through machine learning, where systems improve performance by learning from data rather than following fixed rules. Three main paradigms are typically distinguished. Supervised learning uses historical data, such as past deliveries and costs, to forecast demand or identify efficient routes. Unsupervised learning searches for hidden patterns in unlabelled datasets, for example clustering customer behaviour or transport flows. Reinforcement learning relies on feedback, adjusting routing strategies based on rewards such as lower fuel use or shorter delivery times (Sarker, 2021; Singh et al., 2021).

Alongside machine learning, logistics has traditionally relied on heuristics, that is practical "rules of thumb" that provide workable solutions when exact optimisation is too complex. Simple heuristics include choosing the nearest delivery point, while metaheuristics such as genetic algorithms iteratively improve solutions. These methods can be effective, but they lack adaptability. By combining heuristics with AI, firms gain both speed and flexibility: for instance, AI can guide heuristic algorithms to avoid traffic bottlenecks that static rules would miss (Farooq & Iqbal, 2025).

Together, these approaches enable logistics networks to operate more efficiently and adaptively. Instead of static, one-off planning, AI systems can continuously adjust to real-world conditions, as an essential capability in global value chains shaped by frequent disruptions (Sarker, 2021; Singh et al., 2021).

1.2. Differences from Classical Optimisation Methods

Classical optimisation methods such as linear or integer programming remain useful for stable, well-defined problems but are limited by rigidity. Once solved, they cannot adapt if conditions change. For instance, a model may design an optimal truck route by distance and cost, but if a road is suddenly closed, it cannot recalculate without being solved again from the beginning. Modern navigation systems, such as those in mobile applications, address this challenge by combining classical routing algorithms with real-time data and, increasingly, AI-based predictive analytics to anticipate congestion and dynamically adjust routes (Sarker, 2021).

Demand fluctuations highlight another difference. Deterministic models assume average demand, which leads to inefficiencies when actual demand deviates sharply. AI methods trained on historical and contextual data can anticipate such spikes, for example during holiday sales, and thereby allow more accurate planning (Kimiaei et al., 2025). Scalability is also a challenge for classical methods: in large urban networks with thousands of delivery points, they may require hours of computation, whereas AI models, drawing on past cases, can generate good solutions within minutes (Farooq & Iqbal, 2025).

AI supports multi-objective optimisation. While traditional models minimise cost or time alone, AI can also incorporate environmental criteria such as fuel use, CO_2 emissions, and empty miles, enabling choices that balance efficiency and sustainability.

To better illustrate these differences, Table 1 summarises the main contrasts between classical optimisation methods and AI-driven approaches.

Table 1. Comparison of classical and AI-driven optimisation methods

Dimension	Classical Methods	AI-Driven Methods
Flexibility	Rigid, static once solved	Adaptive, responsive to real-time changes
Environmental integration	Focus on cost/time only	Multi-objective, includes emissions and fuel use
Scalability	Computationally limited in large problems	Learns from past data, scalable to big systems
Risk management	Limited scenario planning	Predictive and dynamic adaptation

1.3. Green Aspect: Reducing CO_2 Emissions, Fuel Consumption, and Empty Miles

A distinctive contribution of AI-driven optimisation lies in its ability to embed sustainability objectives directly into logistics. Research on deep reinforcement learning shows that routing models can minimise both distance and emissions, balancing operational and environmental goals (Xie, 2025). In cold chain logistics, AI-supported planning reduces energy use and carbon output while ensuring service quality (Hu & Wang, 2025). Broader reviews confirm that carbon footprint reduction is increasingly treated as a core optimisation target alongside cost and time (Jahagirdar, 2025), while the digitalisation of value chains is recognised as a key enabler of sustainability transitions (Stanojević & Lichun, 2023).

The problem of empty miles illustrates this well. Vehicles often return without cargo, wasting fuel and capacity. AI systems combining predictive analytics with multimodal planning can better coordinate backhaul opportunities, reducing both unnecessary mileage and emissions (Chen et al., 2025). In this way, AI strengthens operational efficiency while directly supporting the environmental goals of the green transition.

2. APPLICATIONS OF AI IN GREEN SUPPLY CHAINS

2.1. Direct Transport Optimisation

AI applications in direct transport optimisation represent the most immediate way to cut emissions and improve efficiency in global value chains. At the core are route optimisation algorithms that go beyond the simple "shortest path" principle by integrating real-time traffic, weather, and operational data. Unlike static models, AI-driven systems can continuously update routes as conditions change, ensuring fewer kilometers travelled, lower fuel consumption, and reduced emissions.

Urban transport is another key area, where last mile delivery poses significant sustainability challenges. Last mile delivery refers to the final stage of transporting goods from a distribution hub to the end customer, which is often the most costly and carbon-intensive part of logistics because it involves short distances, frequent stops, and high fuel consumption. Dense urban environments amplify these problems, producing congestion and disproportionate CO_2 emissions relative to distance travelled (Saleh et al., 2024). AI-supported systems integrate demand forecasting, traffic prediction, and fleet coordination to improve the efficiency of last mile operations. By reducing unnecessary mileage, minimising idle time in traffic, and optimising delivery schedules, these systems not only cut costs and delays but also facilitate the use of greener transport options such as electric vans and cargo bikes, which become more effective when managed through AI-based planning.

Finally, multimodal logistics benefits from AI tools that select and coordinate between road, rail, and maritime transport. Multimodal logistics refers to the combined use of different modes of transport within a single supply chain, where goods may travel by ship, train, and truck before reaching their final destination. Traditional models often rely on cost or time as decision criteria, whereas AI enables simultaneous consideration of emissions, capacity utilisation, and resilience to disruptions. By guiding the choice of transport mode dynamically, AI systems support a shift to less carbon-intensive options, such as rail over road, without sacrificing reliability.

The case of DHL GoGreen

One of the most prominent corporate initiatives linking artificial intelligence to sustainable logistics is DHL's *GoGreen* programme. DHL applies advanced routing algorithms integrated with digital mapping and real-time traffic data to optimise delivery operations (Boorová et al., 2024). Particular emphasis is placed on urban transport and last-mile delivery, where congestion and a high density of short trips generate disproportionately high emissions. By combining AI-driven route optimisation with the deployment of electric vehicles and bicycles for delivery, DHL has managed to reduce "empty miles" and improve the efficiency of its urban logistics network (Go-Beyond.AI, 2024).

In addition, DHL employs multimodal logistics models supported by AI analytics, combining road, rail, and maritime transport to minimise emissions per ton-kilometre. These AI systems enable dynamic decision-making on transport modes based on network congestion, costs, and environmental objectives, moving beyond static optimisation towards adaptive multimodal planning (DHL Freight Connections, 2024).

The outcomes of such initiatives demonstrate measurable reductions in CO_2 emissions and improvements in delivery accuracy. They also illustrate how AI-driven route optimisation supports both corporate sustainability strategies and compliance with emerging regulatory requirements in the logistics sector (DHL Freight Connections, 2024). As such, the DHL case shows that artificial intelligence, when integrated into transport and logistics operations, can significantly advance the twin goals of efficiency and sustainability in global value chains.

2.2. Predictive analytics

Predictive analytics plays a central role in building greener and more efficient logistics networks. Predictive analytics refers to the use of historical and real-time data, combined with statistical models and machine learning techniques, to forecast future trends such as demand levels, transport flows, or potential disruptions. By processing large datasets, companies can better anticipate fluctuations in demand and align transportation flows accordingly. AI-supported demand forecasting reduces the likelihood of overstocking or understocking, thereby cutting both unnecessary trips and excess inventories. This has direct implications for sustainability, as fewer vehicles are dispatched without full loads and resources are allocated more efficiently.

Recent studies highlight that big data analytics combined with AI, IoT, and predictive modelling can significantly mitigate transportation risks in global value chains (Stanojević, 2025). Predictive route planning allows firms to foresee disruptions such as roadblocks, protests, or military activity, while scenario planning provides the means to adapt to geopolitical shocks including sanctions or trade route closures (Stanojević, 2024). These capabilities demonstrate how advanced analytics lay the groundwork for AI-driven route optimisation, linking risk management with sustainability objectives. Predictive analytics also reduces uncertainty in demand forecasting and resource allocation, while supporting sustainable and circular supply chain models such as reverse logistics for critical materials (Iseri et al., 2025).

Building on this foundation, AI extends predictive analytics beyond forecasting by introducing real-time adaptability through reinforcement learning and dynamic routing algorithms. This enables not only better anticipation of risks but also immediate corrective action, a feature especially valuable in the context of green and efficient global value chains.

The Case of UPS ORION

Predictive analytics has become a cornerstone of sustainable logistics by enabling firms to anticipate demand, optimise vehicle usage, and minimise unnecessary trips. A leading example is UPS's *On-Road Integrated Optimisation and Navigation* (ORION) system, one of the largest AI-driven logistics platforms in operation worldwide.

ORION applies advanced predictive algorithms to analyse data on delivery addresses, traffic conditions, and customer demand in real time. Based on these inputs, it dynamically generates optimal delivery routes that minimise distance travelled while ensuring timely service (BSR, 2023). By incorporating predictive demand modelling, ORION reduces excess vehicle movements and prevents the accumulation of unnecessary inventories across the network.

The environmental and economic outcomes have been substantial. According to company reports, ORION has reduced annual travel by approximately 160 million kilometres, saving an estimated 38 million litres of fuel and preventing over 100,000 metric tons of CO_2 emissions each year (DocShipper, 2024). Beyond its environmental contribution, ORION has enhanced delivery accuracy and reduced operational costs, demonstrating that AI-powered predictive analytics can simultaneously advance efficiency and sustainability.

This case exemplifies how predictive analytics supports green global value chains by linking operational optimisation with environmental responsibility. It shows that the integration of AI allows logistics providers not only to anticipate fluctuations in demand but also to implement adaptive, cost-effective, and low-carbon routing strategies.

2.3. Digital Twins and Simulation

Digital twins and simulation technologies provide advanced tools for planning and managing complex logistics systems under uncertain conditions. A digital twin is a virtual replica of a physical asset or system, such as a warehouse, transport hub, or entire logistics network, that is continuously updated with real-time data from its physical counterpart. This allows managers to test different scenarios, ranging from traffic congestion and weather disruptions to equipment failures, without interrupting real operations. By identifying bottlenecks before they occur, digital twins support more efficient allocation of resources and reduce both delays and emissions.

In logistics, digital twins are particularly valuable for multimodal networks where coordination across road, rail, air, and sea transport is required. Simulation models powered by AI can compare alternative routing or scheduling decisions, optimise terminal operations, and evaluate the impact of infrastructure constraints. These tools are also useful for crisis management, as they allow firms to prepare responses to extreme events such as port closures, strikes, or geopolitical disruptions.

By integrating predictive analytics with real-time monitoring, digital twins contribute directly to sustainability objectives. They help minimise idle time, lower energy use, and support the transition towards greener logistics systems. As recent reviews show, the combination of AI-driven simulation and digital twin technology offers strong potential to enhance both resilience and environmental performance in global supply chains (Chen et al., 2025).

The case of the Port of Rotterdam

The Port of Rotterdam, the largest seaport in Europe, has become a leading example of how digital twin technology can transform logistics operations. By creating a dynamic virtual model of the port's infrastructure, vessel traffic, and cargo flows, managers can simulate different operational and environmental scenarios. This enables more efficient scheduling of ship arrivals, loading and unloading activities, and onward connections with rail and road transport (ArXiv, 2023).

A key advantage lies in the ability to predict and reduce congestion. Real-time data from sensors and AI-driven analytics are fed into the digital twin, allowing operators to identify bottlenecks before they materialise. This reduces waiting times for vessels, lowers fuel consumption from idling ships, and cuts overall CO_2 emissions (iBinder, 2024). In addition, the technology supports contingency planning by modelling responses to extreme weather, labour strikes, or geopolitical shocks.

The Rotterdam case illustrates how digital twins, when integrated with AI, contribute to both operational efficiency and sustainability. By reducing delays, optimising multimodal transfers, and supporting adaptive planning, the port demonstrates that advanced digitalisation is not merely a technical upgrade but also a pathway to greener and more resilient global value chains.

Table 2 provides a comparative overview of the three main areas of AI application discussed in this section, highlighting their key contributions and limitations.

Table 2. Key areas of AI application in green supply chains

Area of Application	**Main Contributions**	**Limitations**
Transport and Logistics	Route optimisation, last mile efficiency, multimodal coordination	Widely applied, but still dependent on data quality
Predictive Analytics	Better demand forecasts, reduced trips and inventories, risk anticipation	Requires integration of diverse datasets
Digital Twins and Simulation	Real-time modelling, bottleneck detection, resilience in crises	High costs, advanced infrastructure needed

3. DISCUSSION AND CONCLUSIONS

The findings of this paper highlight that AI-driven optimisation provides advantages over classical approaches by combining adaptability, scalability, and environmental integration. Unlike traditional models that focus narrowly on cost or time, AI methods enable multi-objective optimisation, allowing firms to simultaneously pursue efficiency and sustainability.

Across the three main areas of application, distinct contributions emerge. Transport and logistics remain the most visible domain, where route optimisation, last mile solutions, and multimodal coordination directly reduce emissions and fuel consumption. Predictive analytics offers strategic benefits by improving demand forecasting and risk anticipation, which in turn lowers unnecessary trips and inventories. Digital twins and simulation provide the most sophisticated capabilities, enabling real-time modelling and crisis preparedness, though their adoption is currently constrained by high costs and infrastructural requirements.

Despite these advantages, several limitations persist. AI-based systems depend heavily on high-quality data, which remains uneven across regions and industries. Implementation costs and the need for specialised expertise present further barriers, particularly for smaller firms. Moreover, regulatory and ethical issues related to data use must be resolved to ensure broader acceptance.

This study shows that AI applications in route optimisation extend beyond operational gains and act as a structural enabler of the green transition in global value chains. They are not only tools for improving efficiency but also mechanisms for building greener and more resilient supply networks. Future research should explore sector-specific case studies, for example in agriculture, transport corridors, or defence logistics, to better understand how AI can balance efficiency, sustainability, and resilience in diverse contexts.

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