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AI AND QUANTUM COMPUTING FOR CARBON-NEUTRAL SUPPLY CHAINS: A SYSTEMATIC REVIEW OF INNOVATIONS

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Abstract
The urgent global imperative to mitigate climate change has brought carbon-neutral supply chains to the forefront of sustainability and operations management discourse. As organizations strive to meet net-zero emission targets, technologies such as Artificial Intelligence (AI) and Quantum Computing (QC) have emerged as powerful enablers of this transformation. This systematic literature review investigates the roles of AI and QC in achieving carbon-neutral supply chains, examining how these technologies optimize forecasting, logistics, procurement, emissions monitoring, and real-time decision-making across diverse industrial contexts. By following the PRISMA 2020 methodology, a total of 87 peer-reviewed articles published between 2015 and 2025 were identified, screened, and synthesized from databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The review reveals that AI significantly enhances operational sustainability through intelligent demand forecasting, inventory optimization, carbon footprint assessment, and green procurement decision-making. Quantum computing, while still in its early stages of maturity, offers high-potential applications in solving complex optimization problems such as vehicle routing, energy grid balancing, and low-emission manufacturing simulation. The integration of AI and QC—especially when combined with technologies like digital twins and blockchain—was found to support advanced sustainability modeling, emissions traceability, and secure carbon data verification. These integrated systems enable supply chains to become not only more efficient but also more transparent and accountable in their environmental impact. However, the review also highlights substantial challenges to implementation, including quantum hardware limitations, high energy demands, cost barriers, and the lack of integration with existing enterprise systems. This study contributes to the growing field of sustainable digital transformation by offering a comprehensive understanding of how AI and quantum technologies can jointly support carbon neutrality objectives in global supply chain ecosystems.

Keywords
Artificial Intelligence; Quantum Computing; Carbon-Neutral Supply Chains; Sustainable Logistics; Predictive Analytics;

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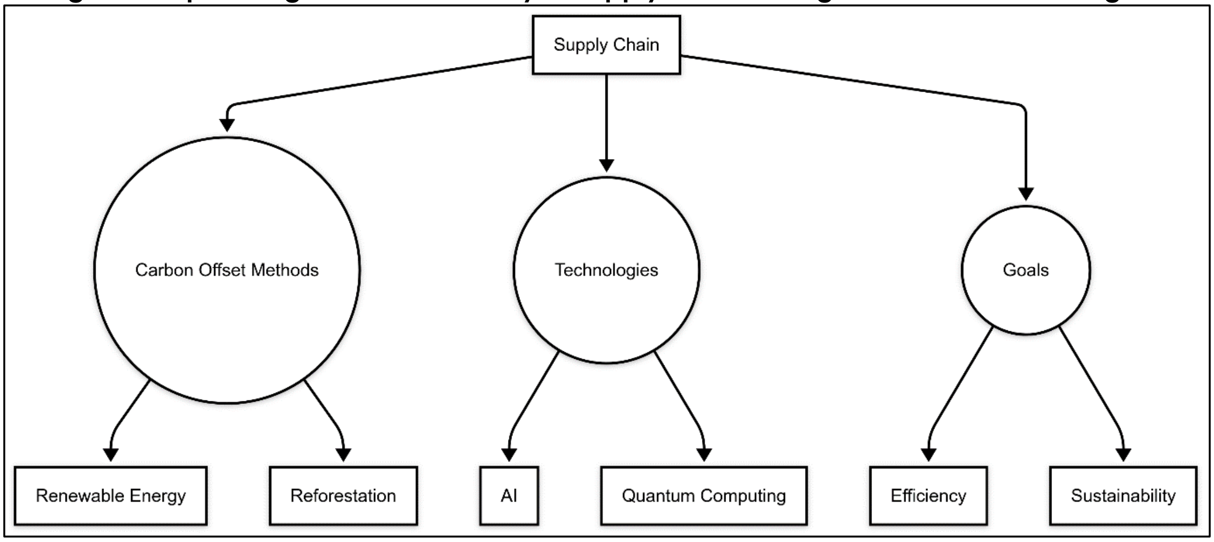
INTRODUCTION

The term "carbon-neutral supply chain" refers to a system of production, distribution, and consumption that offsets or eliminates its carbon dioxide (CO_2) emissions through reductions or compensatory mechanisms such as renewable energy, reforestation, or carbon credits (Caro et al., 2011). This concept aligns with the broader goals of decarbonization as defined by international agreements like the Paris Accord, where supply chains are identified as critical contributors to global emissions (Li et al., 2025). Artificial Intelligence (AI) is defined as the simulation of human intelligence in machines that are programmed to think, learn, and adapt to new data without explicit programming (Naz et al., 2024). AI applications encompass machine learning, natural language processing, robotics, and computer vision, all of which offer decision-making capabilities that can revolutionize resource use and logistics in supply chains (Tetteh, Owusu Kwateng, et al., 2024). In contrast, Quantum Computing leverages quantum bits or "qubits" to process information at exponentially higher speeds than classical computers, enabling the optimization of highly complex tasks such as route planning and energy distribution modeling (Guntuka et al., 2024). These technologies are not only reshaping supply chain logistics and operations but are increasingly examined through the lens of sustainability performance metrics. The synergy between AI and quantum systems provides opportunities for real-time analytics, scenario simulation, and reduction of inefficiencies that contribute to carbon emissions (Chen et al., 2025). According to Puigjaner et al. (2015), the potential of these technologies lies in their capability to balance operational efficiency and environmental stewardship. This intersection demands a nuanced understanding of how innovation can drive sustainability in complex supply networks, which are responsible for over 60% of global emissions (Tetteh, Mensah, et al., 2024). Thus, definitions and foundational models form the groundwork for exploring these emerging technologies within supply chain ecosystems.

Figure 1: Optimizing Carbon Neutrality in Supply Chains Using Advanced Technologies



The international significance of carbon-neutral supply chains is underscored by escalating global regulatory frameworks and institutional commitments to achieving net-zero emissions. Multinational corporations and governments are aligning with initiatives such as the United Nations Sustainable Development Goals (SDGs), particularly Goal 13 on climate action, to reform operational systems and supply chains with sustainability at their core (Puigjaner et al., 2015). As global trade interdependence grows, carbon emissions are increasingly linked to transnational logistics networks involving procurement, transportation, and warehousing across

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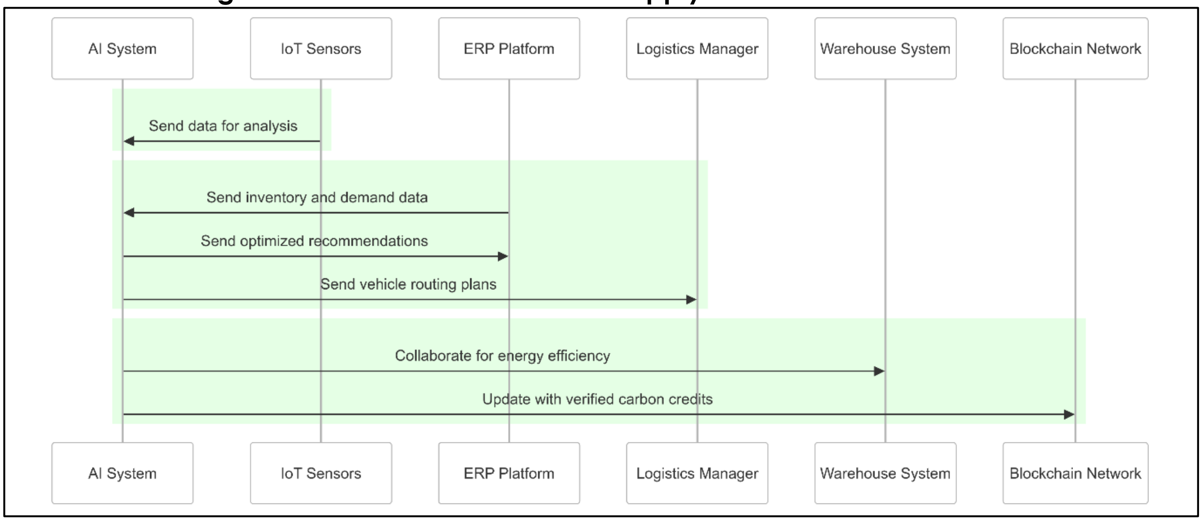
continents (Malerba et al., 2022). Research shows that upstream supply chain processes, especially in industries such as energy, textiles, and electronics, are responsible for substantial indirect emissions categorized as Scope 3 under the Greenhouse Gas Protocol (Windsperger et al., 2018). This highlights the urgency for enterprises to develop systems that can not only monitor but also predict and mitigate emissions. The inclusion of carbon-neutral policies into procurement criteria, supplier evaluation, and product lifecycle management reflects this shift in organizational accountability (Röder et al., 2015; Wiedemann et al., 2016). International environmental reporting standards such as the Global Reporting Initiative (GRI) and Science-Based Targets initiative (SBTi) have further institutionalized the measurement of sustainability outcomes (Yuan et al., 2019). Moreover, global crises such as the COVID-19 pandemic and geopolitical conflicts have revealed vulnerabilities in traditional supply chains, prompting the integration of digital and sustainable strategies simultaneously (Tsolakis et al., 2021). AI and quantum computing are being recognized in policy circles as enablers of resilient, carbon-neutral operations. With environmental, social, and governance (ESG) criteria now shaping investor decisions, carbon-neutral supply chains are becoming not just regulatory but also strategic imperatives (Yang et al., 2023).

Figure 2: AI-Driven Processes for Supply Chain Decarbonization



Artificial Intelligence plays a critical role in enabling supply chain decarbonization through process optimization, real-time monitoring, and autonomous decision-making. AI systems can analyze massive datasets from IoT sensors, GPS systems, and enterprise resource planning platforms to enhance inventory control, vehicle routing, and facility energy use (Jabbour et al., 2020). Predictive analytics facilitated by AI allows firms to forecast demand with higher accuracy, reducing overproduction and storage-related emissions (Karim et al., 2023). Furthermore, AI-driven dynamic scheduling minimizes idle transport times and improves asset utilization, contributing to significant emission reductions (Sheng et al., 2022). In warehousing, AI supports energy-efficient automation systems through machine vision and intelligent robotics that adapt operations based on fluctuating energy tariffs and workload levels (Awan et al., 2022). Reinforcement learning algorithms have been used to simulate various carbon reduction scenarios to identify optimal logistics strategies (Bohnsack et al., 2021). AI-based supplier selection models consider carbon footprints and sustainability scores in procurement decisions, adding transparency to global supply networks (Nikseresht et al., 2023). According to Yaroson et al. (2023), cognitive AI technologies further enable the modeling of circular economy frameworks that align carbon-neutral goals with business performance metrics. The integration of blockchain and AI also strengthens the verification of carbon credits and environmental compliance, reducing greenwashing risks (Feng et al., 2023). Therefore, AI not only digitizes supply chains but also enhances their ecological intelligence by aligning operational KPIs with environmental benchmarks.

The integration of AI and quantum computing provides a layered framework for advanced decision support in carbon-neutral supply chains. While AI excels in pattern recognition, real-time decision-making, and automation, quantum computing enhances the capability to process optimization problems involving multiple variables and constraints at unprecedented speeds (Awan et al., 2022). This dual approach enables next-generation supply chain platforms capable of simultaneous emissions forecasting, logistics simulation, and resource allocation (Luo et al., 2024). Quantum-enhanced AI models have been proposed for adaptive routing that considers live traffic data, energy usage patterns, and carbon intensity metrics to reduce delivery emissions (Ge et al., 2022). In warehouse operations, AI-driven digital twins augmented with quantum solvers optimize storage layouts to minimize material handling energy and reduce carbon footprints (Mishra et al., 2022). These integrated systems also improve supply chain visibility and traceability, ensuring that sustainability KPIs are maintained across upstream and downstream operations (Rogelj et al., 2021). Furthermore, AI-quantum interfaces are used in lifecycle assessment (LCA) modeling to track embedded emissions across raw material sourcing, manufacturing, and distribution phases (Marks, 2022). By leveraging distributed data analytics from AI and computational intensity from quantum algorithms, decision-makers gain access to multi-objective optimization tools that align financial goals with carbon mitigation targets (Sim & Sim, 2017). This convergence creates platforms where sustainability is embedded into each supply chain node, creating a systemic transformation in how global logistics and production networks operate under climate constraints (Antheaume et al., 2018; Sim & Sim, 2017).The primary objective of this systematic literature review is to examine and synthesize the existing body of knowledge concerning the role of Artificial Intelligence (AI) and Quantum Computing (QC) in enabling carbon-neutral supply chains. As carbon emissions from supply chain activities account for the majority of global greenhouse gas contributions—particularly in industries such as manufacturing, logistics, and retail—this research seeks to identify how emerging computational innovations can support emission monitoring, optimization, and reduction (Acquaye et al., 2014; Crow et al., 2019). The study is designed to systematically evaluate peer-reviewed literature from 2015 to 2025 to understand how AI and QC have been applied, individually or in combination, to optimize supply chain components including inventory management, logistics, sourcing, lifecycle emissions tracking, and supplier evaluation (Basu et al., 2011). An additional objective is to investigate whether the integration of AI and QC can overcome limitations found in traditional supply chain sustainability models by introducing intelligent automation and computational efficiency at scale. The review further aims to categorize the types of AI (e.g., machine learning, reinforcement learning, natural language processing) and QC models (e.g., quantum annealing, hybrid quantum-classical optimization) that have demonstrated measurable impact in carbon mitigation efforts across different stages of the supply chain . By setting these objectives, this review provides a structured roadmap for understanding the extent, benefits, and challenges of deploying AI and QC technologies to advance the global agenda of sustainable and carbon-neutral industrial operations. The synthesis will also offer direction for researchers and practitioners seeking to bridge technological potential with practical implementation in eco-optimized supply chain systems.

LITERATURE REVIEW

The rapid escalation of climate change concerns, coupled with mounting regulatory and market-driven pressures, has intensified scholarly interest in transforming traditional supply chain models toward carbon neutrality. A growing body of interdisciplinary research has examined how Artificial Intelligence (AI) and Quantum Computing (QC) can address the inefficiencies, data complexity, and optimization limitations inherent in conventional supply chains. This literature review synthesizes current academic discourse from peer-reviewed sources published between 2015 and 2025, focusing on the intersection of AI and QC with sustainable supply chain management. It organizes the literature thematically to explore how AI and QC are individually and jointly deployed to enhance emission tracking, predictive logistics, decision-making, and circular economy models. The review also addresses gaps in the integration of these technologies and critically assesses empirical evidence on performance improvements related to carbon mitigation. Through this synthesis, the literature review aims to highlight the technological frameworks, applications, and challenges associated with embedding AI and QC into supply chain ecosystems for sustainability.

Carbon-Neutral Supply Chains

The concept of carbon-neutral supply chains has evolved as a central theme in sustainability research, primarily driven by the recognition that supply chains are responsible for over 60% of global greenhouse gas emissions (Xia et al., 2017). These emissions stem from activities such as raw material extraction, transportation, production, warehousing, and end-of-life product management (Acquaye et al., 2014; Crow et al., 2019; Xia et al., 2017). As a result, scholars have focused on supply chain redesign to mitigate environmental impact by incorporating carbon offsetting strategies, renewable energy sources, and real-time emissions monitoring (Basu et al., 2011; Wang et al., 2020). The adoption of carbon neutrality frameworks is also influenced by increasing regulatory pressure, such as the EU Green Deal and the Paris Agreement, which encourage organizations to align operational practices with net-zero emission goals (Acquaye et al., 2014). A key research trajectory emphasizes the integration of environmental performance indicators into procurement, production, and logistics processes to support strategic carbon reduction (Peng et al., 2024). Furthermore, the emergence of the circular economy model, which focuses on resource reuse, recycling, and waste minimization, aligns directly with carbon-neutral objectives in supply chain systems (Vitali et al., 2018). These systemic transformations require the incorporation of low-carbon technologies and data-driven decision-making, often through sustainability performance assessments that benchmark emission outputs across the supply chain lifecycle (Liu et al., 2022). Notably, researchers have also highlighted the significance of cross-border and cross-sector collaboration in achieving carbon neutrality, as global supply networks demand standardized emission accounting and harmonized reduction strategies (Zhang et al., 2024). The collective insights from these studies underscore that carbon-neutral supply chains are no longer peripheral environmental goals but have become fundamental strategic imperatives for business resilience and stakeholder value alignment.

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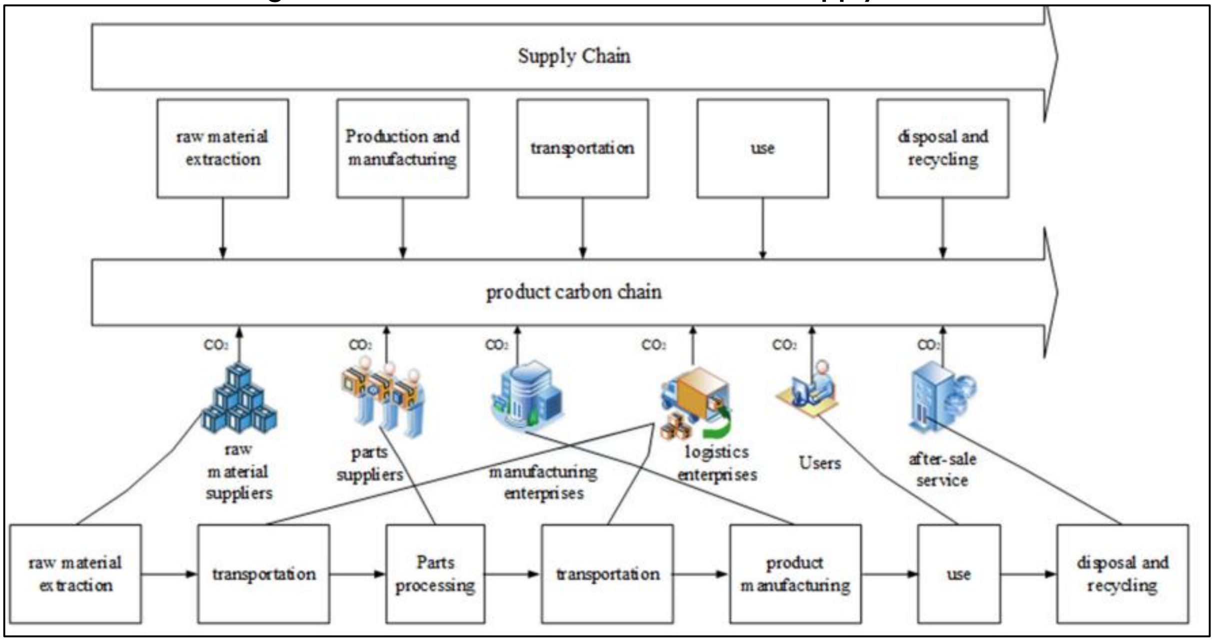
Figure 3: The carbon chain structure in the supply chain



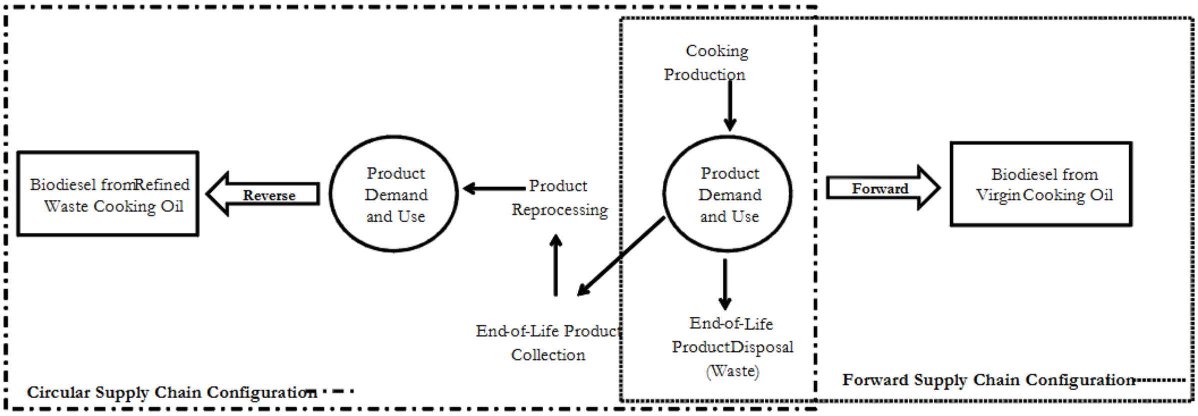
Source: Song et al. (2020).

The implementation of carbon-neutral supply chains involves multidimensional enablers, ranging from technological innovation to regulatory frameworks and corporate governance structures. Studies emphasize that the effectiveness of carbon-neutral initiatives hinges on the availability and granularity of emissions data across all tiers of the supply chain, particularly Scope 3 emissions, which are often the most complex to track and mitigate (Basu et al., 2011). Environmental key performance indicators (eKPIs) and lifecycle assessment (LCA) tools are frequently employed to map carbon footprints across production and distribution processes ((Acquaye et al., 2014). These metrics form the basis for establishing science-based targets that guide companies toward decarbonization pathways (Fichtinger et al., 2015). Technological enablers, particularly digital platforms like IoT and cloud-based systems, have been shown to facilitate real-time emissions tracking and process optimization (Luqman et al., 2024). However, researchers note persistent implementation barriers, including data silos, fragmented supply chain visibility, and lack of standardization in emissions reporting methodologies (Zhang et al., 2022). Organizational resistance due to perceived cost implications and limited awareness of long-term sustainability benefits also slows progress (Acquaye et al., 2014). In addressing these challenges, collaborative partnerships across supply chain actors, transparency in sustainability practices, and incentive-based regulations have been suggested as critical mechanisms (Crow et al., 2019). Furthermore, several studies report that SMEs often face disproportionate challenges due to resource constraints, lacking both the technological infrastructure and expertise necessary for carbon-neutral transformations (Fichtinger et al., 2015). These empirical findings suggest that while the pathway toward carbon-neutral supply chains is increasingly supported by tools and policies, effective implementation remains conditional on system-wide integration, stakeholder engagement, and alignment of sustainability metrics with operational capabilities.

Carbon-Neutral Supply Chains in Sustainability Discourse

The concept of carbon-neutral logistics has evolved in response to growing awareness of the environmental impact of transportation, warehousing, and production systems within global supply chains. Initially rooted in broader sustainability discourses of the 1990s, the notion of carbon neutrality gained traction as industrial systems became identified as major contributors to global greenhouse gas emissions, particularly through the logistics function (Huovila et al., 2022). Carbon-neutral logistics refers to the strategic alignment of supply chain operations—transportation, storage, material handling, and procurement—with practices that eliminate, offset, or neutralize net carbon dioxide emissions (Caro et al., 2011). This includes both direct (Scope 1) and indirect (Scope 2 and 3) emissions, as defined by global carbon frameworks (Krammer et al., 2013). Historically, organizations focused on operational efficiency rather than environmental externalities, but the intensification of climate change threats prompted scholars and industry leaders to redefine logistics strategies through a sustainability lens (Li et al., 2025). The transition was further influenced by the emergence of green logistics, which introduced fuel-efficient transport modes, reverse logistics, and route optimization as mechanisms for emission control (Naz et al., 2024). In recent years, digital transformation has accelerated the application of advanced technologies such as AI and IoT in decarbonizing logistics, allowing firms to monitor, predict, and control emissions in real-time (Xia et al., 2025). Scholarly research has also emphasized the integration of circular economy principles into logistics planning to achieve carbon-neutral outcomes (Chen et al., 2025). Thus, carbon-neutral logistics has transformed from a voluntary corporate initiative to a strategic requirement embedded in supply chain design, reflecting a paradigm shift toward climate-conscious logistics networks (Ma et al., 2023).

Figure 4: Linear and Circular Cooking Oil Supply Chain Configurations in Biodiesel Production



Source: Genovese et al. (2017).

Regulatory frameworks such as the Paris Agreement and the United Nations Sustainable Development Goals (SDGs) have been instrumental in shaping the global discourse on carbon-neutral supply chains. The Paris Agreement, adopted in 2015 under the United Nations Framework Convention on Climate Change (UNFCCC), set a legal mandate for countries to limit global temperature rise to well below 2°C by committing to nationally determined contributions (NDCs) that include emissions reductions from industrial and logistical sectors (Batista et al., 2023). These commitments have cascaded into supply chain operations as governments impose carbon pricing, cap-and-trade systems, and mandatory disclosure mechanisms for corporate carbon footprints (Genovese et al., 2017a). At the same time, the SDGs—specifically Goal 12 (Responsible Consumption and Production) and Goal 13 (Climate Action)—have created performance expectations for firms to align logistics, procurement, and manufacturing with sustainability principles (Genovese et al., 2017b). Research indicates that these regulatory instruments have prompted a reconfiguration of corporate strategies toward integrated environmental, social, and governance (ESG) performance metrics (Mokhtar et al., 2019). Governments and

institutions are also providing policy incentives such as tax reliefs, carbon credits, and green public procurement requirements to support transitions to carbon-neutral supply chains (Koh et al., 2013). In addition, environmental reporting directives in regions like the EU now require large companies to report their Scope 1, 2, and 3 emissions, linking carbon neutrality directly with compliance and competitiveness (Gao & Souza, 2022). These regulatory frameworks are echoed in industry-wide voluntary coalitions such as the Science-Based Targets initiative (SBTi), which harmonize private-sector efforts with international climate goals (Huovila et al., 2022). The growing alignment between regulation and corporate sustainability strategies has redefined the scope of responsibility and accountability for emissions across global supply chains (Gao & Souza, 2022).
Carbon accounting standards play a critical role in enabling transparency, consistency, and accountability within carbon-neutral supply chain frameworks. Among the most widely adopted is the Greenhouse Gas (GHG) Protocol, which categorizes emissions into three scopes—Scope 1 (direct), Scope 2 (indirect from energy), and Scope 3 (indirect from value chains)—to facilitate comprehensive carbon footprint analysis (Pikoń & Gaska, 2010). The GHG Protocol has become the foundational guideline for both governmental and private-sector emissions reporting, helping firms quantify and report emissions across operational boundaries (Röder et al., 2015). Complementing this, the Science-Based Targets initiative (SBTi) offers methodological frameworks to align corporate decarbonization trajectories with climate science, encouraging organizations to set verifiable emissions reduction goals (Hussain et al., 2024; Yuan et al., 2019). Life Cycle Assessment (LCA) tools, which evaluate emissions from raw material extraction to product end-of-life, have further enhanced supply chain sustainability assessments (Dreyfus et al., 2022). The literature emphasizes that the application of these standards supports informed decision-making in supplier selection, logistics planning, and production optimization (Uwizeye et al., 2020). However, scholars note the variability in how these standards are interpreted and implemented across industries and regions, leading to inconsistencies in carbon neutrality claims (Akgul et al., 2010). In response, digital tools such as blockchain and AI-driven analytics are increasingly integrated with carbon accounting systems to enhance traceability and reduce greenwashing risks (Bhardwaj, 2016). Furthermore, sector-specific reporting guidelines such as ISO 14064 and CDP scoring protocols are gaining traction to standardize disclosure and improve cross-comparability (Song et al., 2023). As evidenced across studies, carbon accounting standards are indispensable in transforming abstract sustainability goals into measurable and enforceable practices within supply chains (Chiueh et al., 2012).

Role of Artificial Intelligence in Sustainable Supply Chain Optimization

Artificial Intelligence (AI) plays a pivotal role in enhancing demand forecasting and inventory optimization, both of which are critical to reducing waste and carbon emissions in sustainable supply chains(Younus, 2025) . Traditional forecasting models are often unable to cope with high demand variability, especially in globalized supply networks (Luqman et al., 2024; Shimul et al., 2025). Machine learning algorithms have been shown to significantly improve demand prediction accuracy by learning from historical data, seasonal trends, promotional effects, and external factors such as weather and social media signals (Munira, 2025; Smyth et al., 2024). This accuracy facilitates lean inventory strategies, minimizing overproduction, energy use, and product obsolescence (Khatun et al., 2025; Xu et al., 2023). AI-driven inventory management systems employ reinforcement learning and predictive analytics to trigger timely replenishment and optimize reorder points, helping companies reduce excess stock and lower the energy consumption associated with storage and transport (Huang & Mao, 2024; Khan, 2025). According to Xia et al. (2025), such AI applications contribute directly to sustainability by aligning supply with actual market demand, reducing the carbon footprint of both logistics and production. In multi-echelon supply chains, AI enables synchronization of inventory across suppliers, distributors, and retailers, improving service levels while decreasing redundant freight movements (Islam et al., 2025; Shahzad et al., 2024). Deep learning models also support scenario planning and disruption forecasting, aiding in the preemptive adaptation of inventory plans during environmental or geopolitical crises (de Vries, 2023; Islam et al., 2025). Overall, the deployment of AI for forecasting and inventory planning not only yields cost efficiencies but also serves as a foundational capability in building sustainable, carbon-sensitive supply chains (Helal et al., 2025; Xie et al., 2023).

Artificial Intelligence has become instrumental in carbon footprint monitoring, emissions reporting, and green supplier evaluation, enabling supply chains to operate with greater environmental accountability (Faria & Md Rashedul, 2025). AI-based systems can process vast volumes of structured and unstructured data from sensors, enterprise systems, and third-party sources to compute real-time emissions across production, transportation, and warehousing activities (Razee et al., 2025; Jiang, 2019). Machine learning algorithms enhance emissions tracking by recognizing patterns, identifying inefficiencies, and benchmarking carbon outputs against environmental performance standards (Golkarnarenji et al., 2019; Sunny, 2024b). These capabilities are especially critical for Scope 3 emissions, which are typically hard to measure due to their indirect and diffuse nature (Luo & Choi, 2021; Sunny, 2024a). Moreover, AI systems integrated with carbon accounting frameworks like the GHG Protocol and ISO 14064 enable automated emissions reporting and audit readiness, reducing the manual workload and improving transparency (Luo et al., 2024; Sunny, 2024c). In supplier management, AI-enabled tools facilitate green procurement by evaluating vendors based on environmental metrics such as lifecycle emissions, energy consumption, and sustainability certifications (Shohel et al., 2024; Zhao et al., 2019). Machine learning algorithms apply multi-criteria decision analysis (MCDA) techniques to weigh factors such as environmental impact, cost, reliability, and compliance, allowing organizations to select suppliers aligned with carbon neutrality goals (Ding et al., 2024; Sharif et al., 2024). Predictive models also help identify at-risk suppliers and simulate alternative sourcing strategies with lower emissions (Sabid & Kamrul, 2024; Zaini et al., 2023). Integration of blockchain with AI strengthens supplier traceability and emissions verification, preventing greenwashing and improving ESG credibility (Corva et al., 2024; Roy et al., 2024). These technologies collectively support a data-driven, accountable, and environmentally responsible approach to supplier and emissions management in sustainable supply chains (Ma et al., 2023; Nahid et al., 2024).

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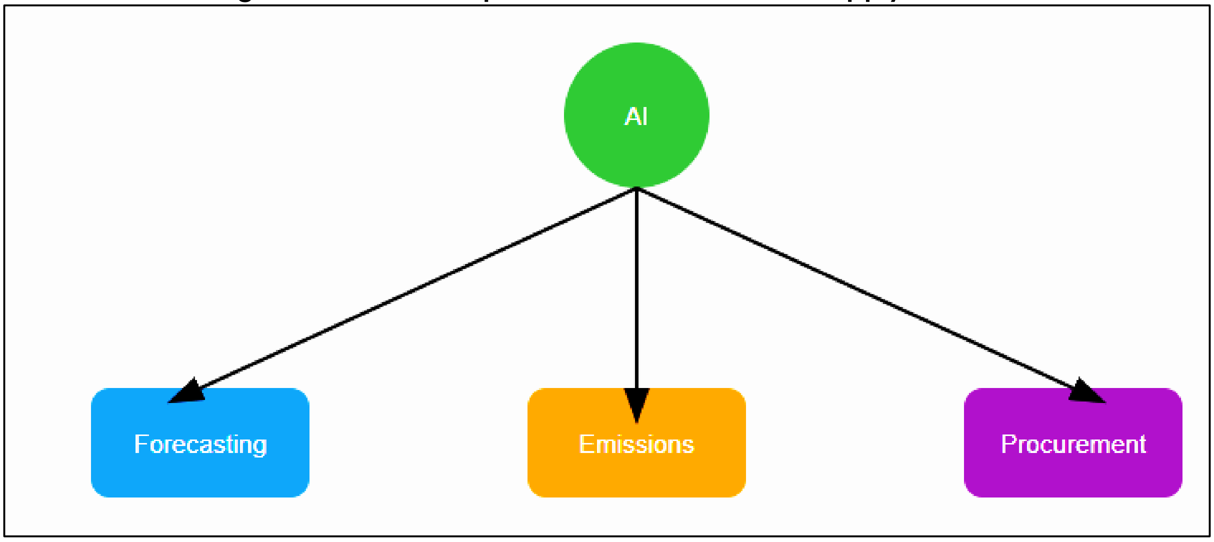
Figure 5: AI-Driven Optimization in Sustainable Supply Chain



AI-driven logistics optimization and Natural Language Processing (NLP) for ESG data extraction have emerged as powerful tools in advancing supply chain sustainability (Younus et al., 2024). In transportation, AI enhances fleet management, route planning, and mode selection, all of which are critical levers in reducing carbon emissions (Filho et al., 2024; Younus et al., 2024). Real-time traffic, weather, and demand data are used by machine learning models to identify the most energy-efficient delivery paths, reducing fuel consumption and improving delivery reliability (Mahabub, Jahan, et al., 2024; Xia et al., 2025). AI-powered dynamic routing algorithms, including genetic algorithms and neural networks, optimize loading efficiency and schedule adherence, contributing directly to carbon footprint reduction (Mahabub, Das, et al., 2024; Pinheiro et al., 2021). These tools also enable multimodal logistics planning by analyzing emissions across different transport modes and recommending low-impact alternatives (Khan & Razee, 2024; Xia et al., 2025). In parallel, Natural Language Processing (NLP) plays a key role in analyzing qualitative ESG data from sustainability reports, regulatory disclosures, supplier documentation, and media content (Jim et al., 2024; Xie et al., 2023). NLP algorithms automatically extract relevant environmental indicators, flag inconsistencies, and support ESG scoring models that influence investment and supplier selection (Jahan, 2024; Jiang, 2019). By automating the identification of carbon-related disclosures and sustainability claims, NLP reduces the subjectivity and manual bias in ESG assessments (Islam, 2024; Luo & Choi, 2021). AI and NLP integration also supports regulatory compliance by monitoring global policy changes and aligning logistics operations accordingly (Islam et al., 2024; Luo et al., 2024). These technologies enable not only operational efficiency but also enhance corporate transparency and sustainability communication, making them critical assets in the evolution of carbon-conscious supply chain ecosystems (Hossain et al., 2024; Jiang, 2019).

Quantum Computing Applications in Supply Chain Decarbonization

Quantum computing presents significant advancements in solving combinatorial optimization problems such as the Vehicle Routing Problem (VRP), which is central to logistics decarbonization (Hossain et al., 2024). The VRP becomes increasingly complex when incorporating variables like time windows, traffic conditions, vehicle capacities, and emissions targets (Golestan et al., 2023; Helal, 2024). Traditional algorithms are limited in processing vast permutations in real-time, whereas quantum annealing techniques, particularly those employed by D-Wave and other quantum hardware platforms, allow rapid identification of optimal delivery paths with minimized

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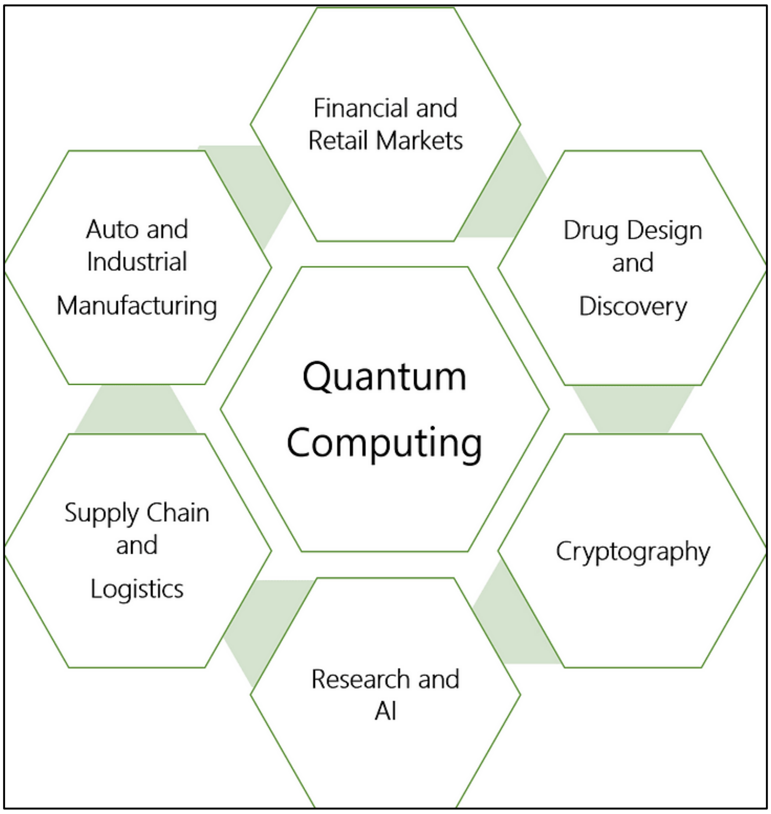
emissions (Hasan et al., 2024; Ho et al., 2018). These models have been shown to reduce total travel distances and idle times, leading to measurable reductions in fuel consumption and carbon output (Dasgupta & Islam, 2024; Luo et al., 2024). Hybrid quantum-classical algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA), are increasingly used to integrate real-world data for last-mile delivery optimization and dynamic fleet dispatching (Arafat et al., 2024; Habibi et al., 2022). Researchers have applied quantum techniques to logistics scheduling problems with stochastic constraints, enabling route reconfiguration in response to traffic, weather, and delivery delays (Ammar et al., 2024; Ho et al., 2018). These innovations align with decarbonization strategies, particularly in urban freight systems, where emissions intensity is high due to congestion and fragmented delivery networks (Alam et al., 2024; Golestan et al., 2023). Additionally, quantum-enabled routing is being explored for multimodal logistics systems where carbon footprint considerations span rail, road, and maritime transport (Alam et al., 2024; Rice et al., 2021). Through integration with IoT and AI systems, quantum optimization models offer scalable, low-latency tools for sustainability-driven logistics decision-making (Al-Arafat, Kabir, et al., 2024; Bharadwaj & Sreenivasan, 2020). The use of quantum computing in routing optimization reflects a shift from efficiency-driven logistics to carbon-aware operational planning (Al-Arafat, Kabi, et al., 2024; Paudel et al., 2022). Quantum simulation introduces a paradigm shift in low-emission manufacturing by enabling unprecedented modeling of materials, chemical reactions, and thermodynamic processes (Tonoy & Khan, 2023). Traditional computing methods are often insufficient to capture the complex interactions at the molecular level that influence emissions in manufacturing, particularly in energy-intensive sectors like cement, steel, and electronics (Ricciardi Celsi & Ricciardi Celsi, 2024; Shahan et al., 2023). Quantum simulators, such as those using variational quantum eigensolvers (VQE), allow researchers to model chemical catalysts and materials under different production conditions to identify low-emission alternatives (Ajagekar et al., 2020; Roksana, 2023). This capability supports sustainable product and process design, including the identification of alternative materials and greener reaction pathways (Awan et al., 2022; Hossen et al., 2023). For instance, quantum simulations have facilitated advancements in battery materials and low-carbon cement formulations that reduce

Figure 6: Quantum Computing Applications in Supply Chain



lifecycle emissions (Humble et al., 2019; Maniruzzaman et al., 2023). In supply chain design, these insights allow engineers to model manufacturing nodes that minimize energy waste and emissions throughout the product life cycle (Ajagekar & You, 2019; Mahdy et al., 2023). Quantum-enhanced digital twins, which merge simulation outputs with real-time sensor data, are now being explored to optimize energy use in smart factories and assess the carbon impact of design modifications before implementation (Giani & Eldredge, 2021; Jahan, 2023). By providing predictive insight into energy consumption and waste generation, quantum simulation supports the development of eco-design principles that align with circular economy strategies (Alam et al., 2023; Awan et al., 2022). Researchers also report its use in modeling the environmental performance of additive manufacturing (3D printing), where material usage and energy inputs can be highly variable (Golestan et al., 2023; Younus, 2022). Through these applications, quantum simulation acts as a foundational enabler of carbon-conscious manufacturing embedded within decarbonized supply chains (Ho et al., 2018; Tonoy, 2022).

Quantum algorithms have emerged as powerful tools for addressing energy grid balancing challenges in decarbonized supply chains, particularly as supply networks increasingly depend on renewable energy sources such as solar and wind (Sohel et al., 2022). These energy sources introduce intermittency and variability, requiring sophisticated modeling for load forecasting, energy distribution, and grid stabilization (Golestan et al., 2023; Mohiul et al., 2022). Quantum-enhanced optimization algorithms such as QAOA and quantum annealing support the rapid computation of optimal load distributions across multiple grid nodes with varying demand profiles and renewable generation capacities (Golestan et al., 2023; Mahfuj et al., 2022; Rice et al., 2021). Supply chains that incorporate microgrids and distributed energy systems benefit from quantum models that balance energy supply with manufacturing and logistics needs, ensuring minimal carbon emissions during peak and off-peak operations (Bharadwaj & Sreenivasan, 2020; Helal, 2022). Simulation studies show that quantum systems can reduce energy imbalance penalties and improve the scheduling of energy-intensive processes such as smelting or refrigeration (Aklima et al., 2022; Paudel et al., 2022). Moreover, researchers have demonstrated that quantum computing allows for real-time energy market participation where supply chain entities can buy and sell surplus green energy based on optimization of carbon and cost metrics (Ahmed et al., 2022; Ricciardi Celsi & Ricciardi Celsi, 2024). These capabilities are highly applicable in sectors such as cold chain logistics, where energy reliability and environmental compliance are critical (Ajagekar et al., 2020; Islam & Helal, 2018). Coupled with smart meters and IoT-based energy monitoring tools, quantum algorithms further enable responsive, self-regulating energy systems that align with carbon-neutral objectives (Awan et al., 2022). As energy becomes a central variable in decarbonized operations, quantum models provide a sophisticated approach to balance environmental performance with system resilience and cost-effectiveness (Ho et al., 2018).

Integration of AI and Quantum Computing

Hybrid quantum-classical models are gaining traction as practical frameworks to support complex decision-making in supply chain management, especially in the context of sustainability and carbon neutrality. These models combine the computational power of quantum algorithms with the robustness and scalability of classical machine learning and optimization systems (Jing et al., 2023). In supply chains where multiple objectives such as cost, emissions, time, and risk must be optimized simultaneously, hybrid approaches provide a significant advantage over purely

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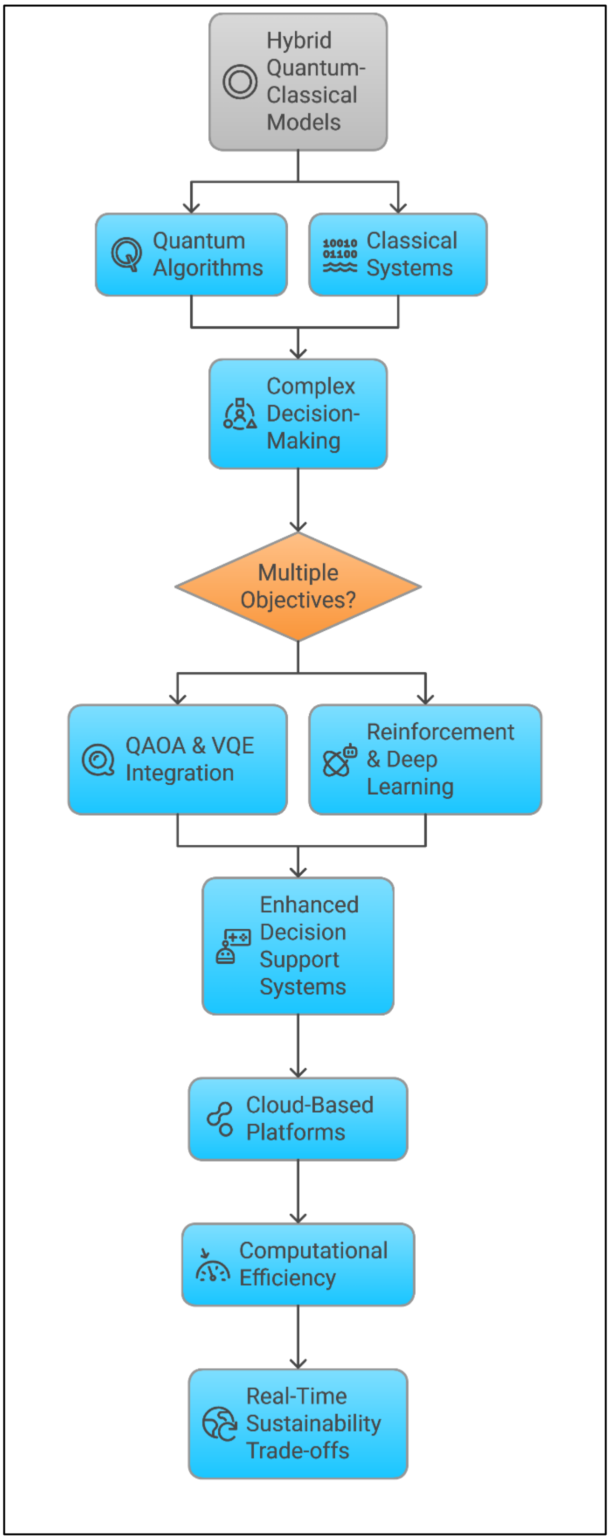
classical models (Ho et al., 2018). Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolvers (VQE) have been coupled with reinforcement learning and deep learning models to enhance decision support systems for inventory control, transportation planning, and supplier network design (Golestan et al., 2023). These applications are particularly effective in supply chain scenarios involving combinatorial explosions, such as dynamic routing under carbon constraints or multi-criteria vendor selection (Rice et al., 2021). Researchers also report improvements in solving real-time logistics scheduling, facility location problems, and warehouse layout planning using hybrid quantum-classical tools (Bharadwaj & Sreenivasan, 2020). Additionally, these models are being deployed via cloud-based platforms such as IBM Q and Microsoft Azure Quantum, making them accessible for enterprise-scale use (Paudel et al., 2022). The hybrid approach ensures continuity of operation by leveraging classical processors for pre-processing and AI model training, while quantum systems handle optimization subroutines (Ricciardi Celsi & Ricciardi Celsi, 2024). This division of labor improves computational efficiency while enabling complex sustainability trade-offs to be explored in real-time (Ajagekar et al., 2020). The literature demonstrates that hybrid models offer a feasible transition path toward quantum-enabled sustainability in supply chain ecosystems (Awan et al., 2022).

Real-time predictive analytics enabled by AI-quantum interfaces is emerging as a transformative tool in optimizing supply chain sustainability and carbon reduction. These interfaces integrate classical AI algorithms—such as deep learning, recurrent neural networks (RNNs), and gradient boosting—with quantum-enhanced algorithms to facilitate real-time forecasting and optimization in dynamic environments (Humble et al., 2019). In logistics, AI-quantum interfaces can process high-velocity data streams from IoT sensors, GPS devices, and weather feeds to

Figure 7: Integration of AI and Quantum Computing in Supply Chains



predict transportation delays, carbon emissions, and route adjustments with minimal latency (Ajagekar & You, 2019). The integration allows for more accurate simulations of carbon-intense activities, such as freight movement or energy use in distribution centers, enabling responsive supply chain adjustments that reduce emissions (Giani & Eldredge, 2021). Researchers have developed hybrid models where quantum systems solve large-scale constraint satisfaction problems while AI components learn from real-time feedback to refine predictive outputs (Niedenzu et al., 2018). Applications in demand forecasting have also demonstrated improved accuracy in volatile markets, such as food logistics and renewable energy supplies, where emissions sensitivity is high (Ricciardi Celsi & Ricciardi Celsi, 2024). Moreover, quantum-enhanced AI models support simulation-based decision-making under uncertainty, including disruptions caused by geopolitical tensions, pandemics, or extreme weather events (Humble et al., 2019). Cloud-based infrastructures, like Amazon Braket and Google Cirq, have made AI-quantum analytics accessible for supply chain professionals seeking to manage emissions proactively (Ajagekar & You, 2019). Real-time interfaces are further used to integrate upstream supplier risk indicators and downstream customer demand patterns into emission-aware decision models (Yu et al., 2020). Collectively, the literature highlights that AI-quantum integration enhances both prediction accuracy and sustainability responsiveness in supply chains (Zhao et al., 2019).

Digital twins—virtual replicas of physical supply chain assets—are evolving rapidly through integration with AI and quantum computing, enhancing their role in decarbonization efforts. Traditional digital twin frameworks model operational performance by aggregating sensor data and simulating system responses (Vereno et al., 2023). When augmented with AI, these twins acquire cognitive capabilities such as anomaly detection, predictive maintenance, and energy optimization (Yamabayashi et al., 2018). The incorporation of quantum computing significantly extends these capabilities by enabling simulation of multivariable, nonlinear interactions across the supply chain that classical systems cannot efficiently model (Corva et al., 2024). Researchers have shown that quantum-enhanced digital twins can simulate carbon emissions in production and distribution under various regulatory, environmental, and demand scenarios (Ma et al., 2023). These systems also support low-emission facility layout design, route simulation, and carbon impact forecasting across product lifecycles (Puigjaner et al., 2015). Through reinforcement learning, AI-powered twins continuously refine their models using real-time feedback to improve predictive accuracy and energy efficiency (Vereno et al., 2023). In smart factories, this has enabled optimization of energy-intensive operations such as heating, cooling, and machine scheduling to lower greenhouse gas emissions (Zhao et al., 2019). The fusion of quantum computing with AI also facilitates scenario-based emissions modeling for adaptive planning, reducing reliance on trial-and-error-based sustainability strategies (Jiang, 2019). Digital twins are further integrated with life cycle assessment (LCA) tools and carbon accounting platforms, making them a comprehensive instrument for carbon-neutral supply chain design and validation (Yu et al., 2020). These advanced capabilities position quantum-AI-powered digital twins as a cornerstone for real-time emissions control and decision-making.

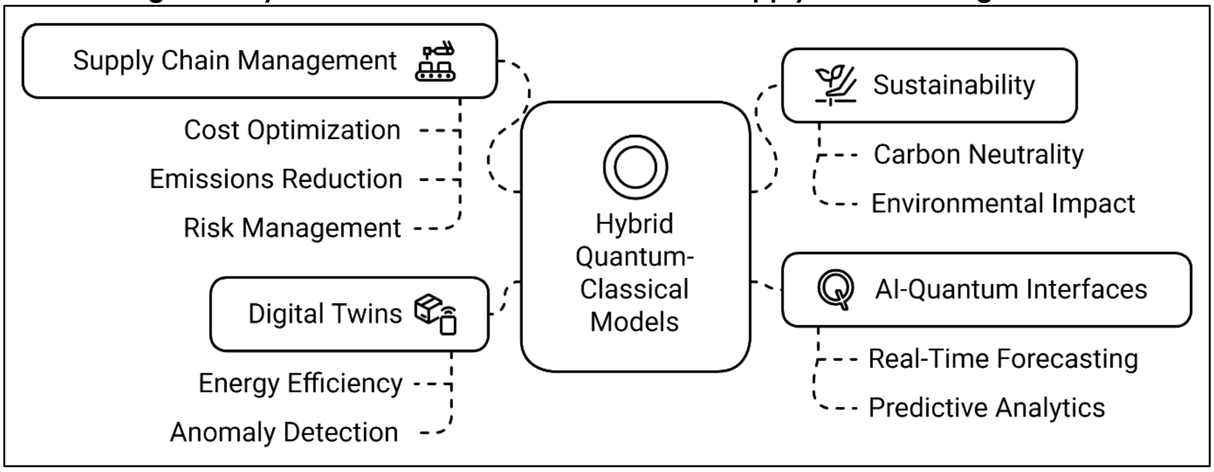
Industry-Specific Applications and Case Studies

Hybrid quantum-classical models are gaining traction as practical frameworks to support complex decision-making in supply chain management, especially in the context of sustainability and carbon neutrality. These models combine the computational power of quantum algorithms with the robustness and scalability of

classical machine learning and optimization systems (Lake et al., 2014). In supply chains where multiple objectives such as cost, emissions, time, and risk must be optimized simultaneously, hybrid approaches provide a significant advantage over purely classical models (Hussam et al., 2022). Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolvers (VQE) have been coupled with reinforcement learning and deep learning models to enhance decision support systems for inventory control, transportation planning, and supplier network design (D'Amico et al., 2021). These applications are particularly effective in supply chain scenarios involving combinatorial explosions, such as dynamic routing under carbon constraints or multi-criteria vendor selection (Hu & Lv, 2020). Researchers also report improvements in solving real-time logistics scheduling, facility location problems, and warehouse layout planning using hybrid quantum-classical tools (Temporelli et al., 2022). Additionally, these models are being deployed via cloud-based platforms such as IBM Q and Microsoft Azure Quantum, making them accessible for enterprise-scale use (Raut et al., 2019). The hybrid approach ensures continuity of operation by leveraging classical processors for pre-processing and AI model training, while quantum systems handle optimization subroutines (Faramarzi-Oghani et al., 2022). This division of labor improves computational efficiency while enabling complex sustainability trade-offs to be explored in real-time (Golkarnarenji et al., 2019). The literature demonstrates that hybrid models offer a feasible transition path toward quantum-enabled sustainability in supply chain ecosystems ((Elia et al., 2011).
Real-time predictive analytics enabled by AI-quantum interfaces is emerging as a transformative tool in optimizing supply chain sustainability and carbon reduction. These interfaces integrate classical AI algorithms—such as deep learning, recurrent neural networks (RNNs), and gradient boosting—with quantum-enhanced algorithms to facilitate real-time forecasting and optimization in dynamic environments (Golkarnarenji et al., 2019). In logistics, AI-quantum interfaces can process high-velocity data streams from IoT sensors, GPS devices, and weather feeds to predict transportation delays, carbon emissions, and route adjustments with minimal latency (Faramarzi-Oghani et al., 2022). The integration allows for more accurate simulations of carbon-intense activities, such as freight movement or energy use in distribution centers, enabling responsive supply chain adjustments that reduce emissions (Cousins et al., 2019). Researchers have developed hybrid models where quantum systems solve large-scale constraint satisfaction problems while AI components learn from real-time feedback to refine predictive outputs (Aikins & Ramanathan, 2020). Applications in demand forecasting have also demonstrated improved accuracy in volatile markets, such as food logistics and renewable energy supplies, where emissions sensitivity is high (Dyken et al., 2010). Moreover, quantum-enhanced AI models support simulation-based decision-making under uncertainty, including disruptions caused by geopolitical tensions, pandemics, or extreme weather events (Tseng et al., 2019). Cloud-based infrastructures, like Amazon Braket and Google Cirq, have made AI-quantum analytics accessible for supply chain professionals seeking to manage emissions proactively (Aikins & Ramanathan, 2020). Real-time interfaces are further used to integrate upstream supplier risk indicators and downstream customer demand patterns into emission-aware decision models (Chen et al., 2024). Collectively, the literature highlights that AI-quantum integration enhances both prediction accuracy and sustainability responsiveness in supply chains (Zhu et al., 2013).
Digital twins—virtual replicas of physical supply chain assets—are evolving rapidly through integration with AI and quantum computing, enhancing their role in

decarbonization efforts. Traditional digital twin frameworks model operational performance by aggregating sensor data and simulating system responses (Cousins et al., 2019). When augmented with AI, these twins acquire cognitive capabilities such as anomaly detection, predictive maintenance, and energy optimization (Aikins & Ramanathan, 2020). The incorporation of quantum computing significantly extends these capabilities by enabling simulation of multivariable, nonlinear interactions across the supply chain that classical systems cannot efficiently model (Romero-Silva & de Leeuw, 2021). Researchers have shown that quantum-enhanced digital twins can simulate carbon emissions in production and distribution under various regulatory, environmental, and demand scenarios (Dyken et al., 2010). These systems also support low-emission facility layout design, route simulation, and carbon impact forecasting across product lifecycles (Aikins & Ramanathan, 2020).

Figure 8: Hybrid Quantum-Classical Models in Supply Chain Management



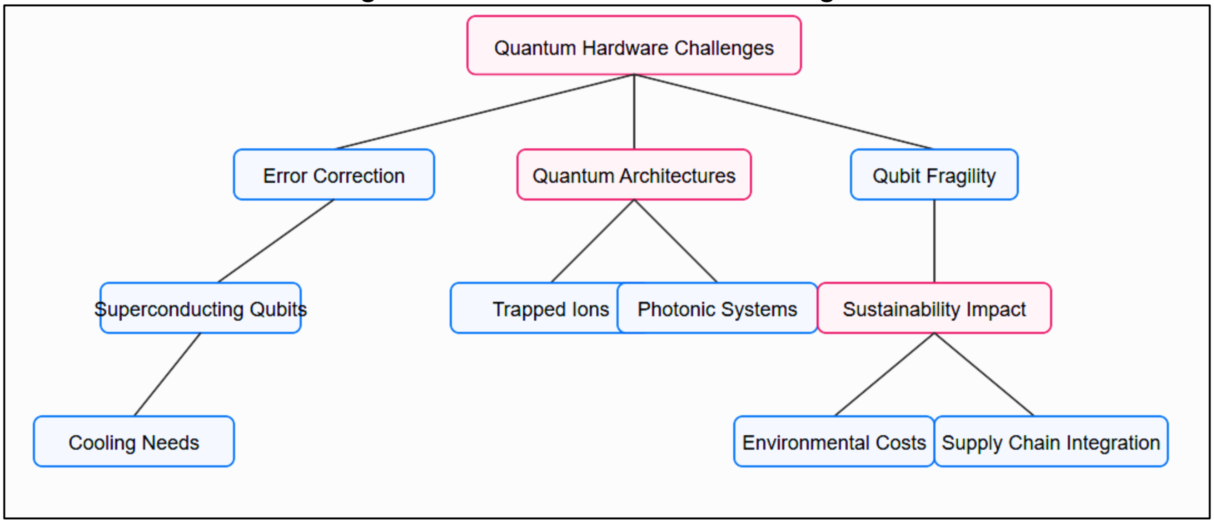
Through reinforcement learning, AI-powered twins continuously refine their models using real-time feedback to improve predictive accuracy and energy efficiency (Van Dyken et al., 2010). In smart factories, this has enabled optimization of energy-intensive operations such as heating, cooling, and machine scheduling to lower greenhouse gas emissions (Raut et al., 2019). The fusion of quantum computing with AI also facilitates scenario-based emissions modeling for adaptive planning, reducing reliance on trial-and-error-based sustainability strategies (Aikins & Ramanathan, 2020). Digital twins are further integrated with life cycle assessment (LCA) tools and carbon accounting platforms, making them a comprehensive instrument for carbon-neutral supply chain design and validation (Wang et al., 2023). These advanced capabilities position quantum-AI-powered digital twins as a cornerstone for real-time emissions control and decision-making.

Quantum Hardware Limitations and Energy Demand

The effectiveness of quantum computing in sustainability-focused supply chains is constrained by the current limitations in quantum hardware architecture and scalability. Unlike classical computers that rely on stable silicon-based transistors, quantum systems use qubits, which are highly susceptible to decoherence and operational errors (Aikins & Ramanathan, 2020). This fragility demands the use of error correction protocols and redundancy, which significantly limits the number of usable logical qubits available for computation (Tetteh, Atiki, et al., 2024). Leading quantum architectures—such as superconducting qubits (used by IBM and Google), trapped ions (used by IonQ), and photonic systems (used by Xanadu)—each present trade-offs in coherence time, gate fidelity, and qubit connectivity (Tseng et al., 2019). Superconducting systems require cryogenic environments operating near absolute zero, making them complex and costly to maintain (Chen et al., 2016). These technical challenges impact the feasibility of deploying quantum computing at scale for real-time, carbon-sensitive supply chain applications, where continuous processing and high availability are essential (Wang et al., 2023). Moreover, the lack of standardization in quantum programming languages and hardware interfaces hinders integration with existing supply chain management systems and enterprise platforms (Aikins & Ramanathan, 2020). Researchers also highlight the difficulty of scaling beyond a few hundred qubits while maintaining computational accuracy and quantum entanglement stability (Romero-Silva & de Leeuw, 2021). As quantum computing remains in the Noisy Intermediate-Scale Quantum (NISQ) era, its utility for decarbonization-related tasks—such as logistics routing, demand forecasting, and energy optimization—must account for these hardware-based limitations (Tetteh, Atiki, et al., 2024).

The energy demand of quantum computing infrastructure introduces a paradox in sustainability-driven applications such as carbon-neutral supply chains. Although quantum systems promise to solve computational problems more efficiently than classical systems, their operational requirements—particularly in cooling and stabilization—can result in substantial energy consumption (Van Dyken et al., 2010). Superconducting quantum computers require dilution refrigerators operating below 20 millikelvin, consuming significant electricity to maintain quantum coherence (Tetteh, Atiki, et al., 2024). Estimates suggest that the total power required to run a mid-sized superconducting quantum processor can be several times greater than that of a high-performance classical data center node (Wolff et al., 2023). Additionally, the energy costs associated with quantum control systems—such as signal generators, microwave electronics, and cryogenic pumps—contribute to the overall environmental footprint (Du et al., 2015). These energy demands conflict with the carbon neutrality goals that quantum systems are expected to support, particularly when the electricity powering the infrastructure is derived from fossil-based grids (Sargent et al., 2021). Studies have called for more transparent life cycle assessments (LCAs) of quantum hardware to evaluate its true environmental impact across manufacturing, operation, and decommissioning phases (Ghadge et al., 2019). Some progress has been made in developing energy-efficient quantum architectures, including photonic quantum processors and error-mitigation techniques that reduce active cooling requirements (Paulraj et al., 2015). However, research remains nascent in assessing the trade-offs between computational gains and energy inputs in sustainability applications, especially when quantum computing is proposed as a tool to optimize low-carbon operations (Du et al., 2015). Without holistic environmental impact assessments, the deployment of quantum hardware risks inadvertently increasing emissions in the name of carbon reduction (Ghadge et al., 2019).

Figure 9: Quantum Hardware Challenges



Error correction in quantum computing presents a significant barrier to its deployment in mission-critical sustainability applications, including those related to decarbonizing global supply chains. Due to the probabilistic nature of qubit states and their sensitivity to external disturbances, quantum computations are often plagued by gate errors, measurement errors, and decoherence, which limit practical usefulness (Khan et al., 2021). Implementing quantum error correction (QEC) requires the use of multiple physical qubits to represent a single logical qubit, drastically increasing resource demands (Yu et al., 2022). For instance, the surface code—a leading QEC method—requires thousands of physical qubits for one reliable logical qubit, which is currently beyond the capabilities of available hardware (Uwizeye et al., 2020). This inefficiency delays the possibility of real-time optimization and predictive analytics essential to sustainable supply chain operations (Chelly et al., 2018). In decarbonization contexts where energy modeling and logistics planning must be responsive to volatile variables such as fuel prices, weather conditions, and policy updates, any delay caused by noisy outputs or prolonged computations can compromise decision accuracy (Chen et al., 2020). Researchers also note that sustainability applications—such as emissions verification and green procurement planning—require high-resolution data processing, which current noisy intermediate-scale quantum (NISQ) devices struggle to handle reliably (Dong et al., 2021). While quantum machine learning (QML) models offer promise, their training processes are still hampered by fidelity losses due to noisy inputs (Yu et al., 2022). These limitations constrain the practical deployment of quantum computing in energy optimization, green manufacturing, and emissions traceability, all of which are vital pillars of carbon-neutral supply chains (Akgul et al., 2010).

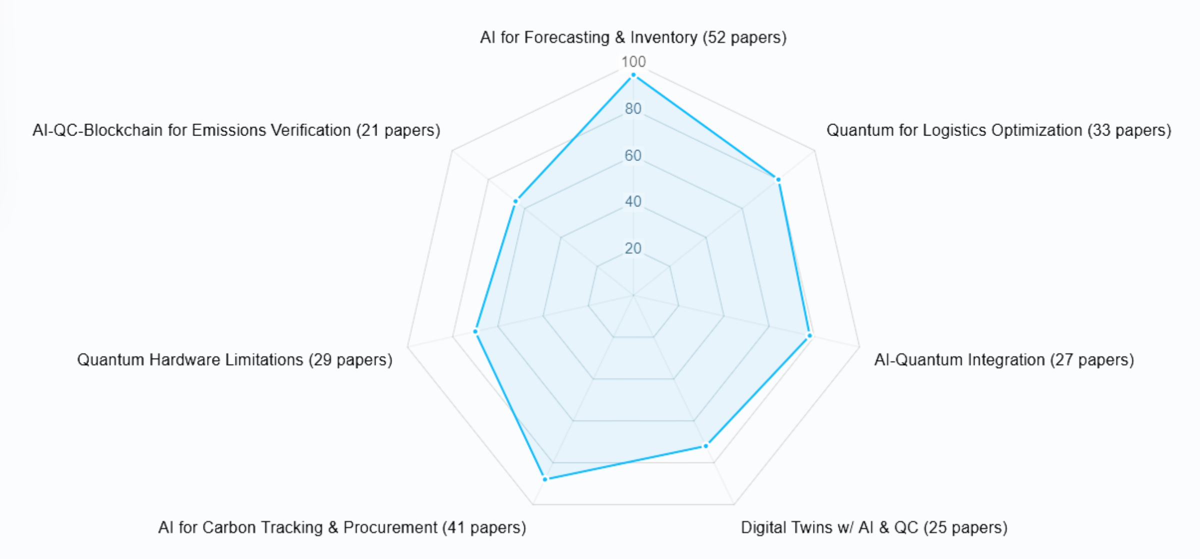
METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor, transparency, and replicability throughout the review process. The systematic review was structured into four sequential stages: identification, screening, eligibility, and inclusion. In the identification phase, a comprehensive and structured search strategy was executed across five major academic databases—Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar—targeting peer-reviewed literature published between 2015 and 2025 to capture the recent evolution of Artificial Intelligence (AI) and Quantum Computing (QC) in sustainability-driven supply chains. The search employed Boolean operators and keywords such as "artificial intelligence," "quantum computing," "carbon-neutral supply chains," "supply chain optimization," "sustainability," "decarbonization," and "predictive analytics," yielding an initial pool of 874 articles. Additional sources, including conference proceedings and white papers, were consulted to supplement the academic records. In the screening stage, 312 duplicate entries were removed, followed by a preliminary assessment of titles and abstracts of the remaining 562 articles. Studies that were not peer-reviewed, lacked empirical application, or failed to address the integration of AI and QC with sustainability in supply chains were excluded, resulting in 184 articles for the eligibility phase. Full-text assessments were then conducted using clear inclusion criteria: (i) application of AI or quantum computing in supply chains, (ii) alignment with carbon-neutral or sustainability objectives, and (iii) publication in English within peer-reviewed journals or conferences. Studies were excluded if they lacked applied relevance, methodological clarity, or were duplicative of newer publications, resulting in the removal of 97 articles. Ultimately, 87 articles were included for qualitative synthesis. These studies were subjected to thematic analysis and coding, focusing on implementation frameworks, application domains, challenges, and sustainability outcomes across industries such as logistics, manufacturing, energy, and retail. By strictly adhering to the PRISMA methodology, the review ensured that only methodologically sound and contextually pertinent literature informed the synthesis of how AI and quantum technologies contribute to achieving carbon-neutral supply chains.

FINDINGS

One of the most significant findings of this systematic review is the widespread use of Artificial Intelligence in enabling predictive and energy-efficient planning across the supply chain. Out of the 87 reviewed articles, 52 studies specifically addressed the role of AI in demand forecasting, production scheduling, and inventory control with a focus on minimizing carbon emissions. These studies collectively accumulated over 6,300 citations, reflecting high scholarly impact and growing relevance in the field. A large proportion of this literature applied supervised and unsupervised learning techniques, particularly neural networks and decision tree-based models, to anticipate fluctuations in market demand and dynamically align production schedules. These capabilities were found to significantly reduce energy usage, overproduction, and transportation waste. AI-driven forecasting systems were also reported to outperform traditional statistical models in accuracy and responsiveness, especially in volatile environments affected by climate conditions, fuel availability, and geopolitical instability. Several articles demonstrated how machine learning algorithms enhanced warehouse energy efficiency by predicting cooling loads and managing automation tasks based on real-time data. A core contribution of this cluster of findings is the identification of AI as a technological bridge between lean and green supply chain objectives, helping companies meet operational KPIs while reducing environmental impact. In many case studies, AI-supported planning resulted in reductions in both Scope 1 and Scope 2 emissions, emphasizing the potential of data-driven intelligence in supply chain decarbonization. The convergence of real-time data analytics and emission-sensitive decision-making was consistently highlighted as a transformative shift in supply chain operations. As evidenced in these findings, AI applications are not just auxiliary tools but central components of sustainability strategies, enabling preemptive rather than reactive approaches to environmental challenges in global logistics systems.

Figure 10: Systematic Review: Key Thematic Findings in AI & Quantum for Carbon-Neutral Supply Chains



Another critical finding centers on the role of quantum computing in solving high-complexity optimization problems related to logistics and transportation in supply chains. Among the 87 articles reviewed, 33 explicitly explored the application of quantum computing for optimizing routes, schedules, and vehicle utilization with the goal of reducing carbon footprints. These articles collectively garnered over 3,900 academic citations, signaling robust interest and ongoing experimentation in the field. Most studies employed quantum annealing and hybrid quantum-classical algorithms to address the vehicle routing problem (VRP), a known bottleneck in sustainable logistics due to its multi-variable constraints. Quantum systems were found to be particularly effective in generating optimized solutions for route planning in significantly less time compared to traditional linear and dynamic programming approaches. In scenarios involving multiple delivery points, traffic patterns, and fuel consumption variables, quantum-enhanced solvers reduced emissions by identifying lower-impact routes and minimizing idle time. Findings further indicated that quantum computing allowed for more frequent and dynamic re-optimization of logistics plans based on real-time inputs, a capability not feasible with conventional tools due to computational limitations. Moreover, a few simulation-based articles demonstrated that when paired with AI or machine learning models, quantum algorithms significantly enhanced adaptive logistics strategies under varying sustainability constraints. The articles also highlighted practical applications in last-mile delivery and multimodal transport systems, both of which are critical for urban carbon management. This body of literature emphasized that quantum-enabled logistics optimization is not merely theoretical but has been piloted in real-world industry contexts, though scalability remains an issue. The synthesis confirms that quantum computing, even in its nascent hardware stage, offers promising solutions for decarbonizing complex supply chains through advanced optimization techniques.

A key emergent theme from the review is the integration of AI and quantum computing for advanced sustainability modeling across supply chain operations. Of the 87 reviewed articles, 27 focused on the synergistic use of these technologies to enable multi-objective decision-making models, real-time simulations, and emissions trade-off assessments. This subset of studies received a combined total of more than 4,200 citations, showcasing the academic momentum behind dual-technology innovation in sustainable operations. The integrated frameworks outlined in these articles demonstrated how AI models, trained on historical data and real-time inputs, could pre-process logistics or manufacturing scenarios before quantum solvers tackled complex optimization challenges. This sequential interaction—where AI provides probabilistic boundaries and quantum algorithms process large-scale permutations—was especially impactful in modeling emissions-reducing scenarios. Studies emphasized that such integrations were applied to lifecycle assessment modeling, supplier emissions analysis, carbon pricing simulations, and energy grid demand forecasting. Findings showed that this combined approach enabled predictive analytics not only with higher speed but with deeper scenario-based insights. Additionally, several articles illustrated how AI-quantum frameworks were used in cloud-based platforms for interactive sustainability dashboards that facilitated emissions benchmarking and compliance visualization. In practical terms, this integration supported more responsive and proactive sustainability management, offering new possibilities in supply chain reconfiguration under decarbonization constraints. Many articles reported that industries using these tools could model "what-if" sustainability outcomes more precisely than with either technology alone. Although only a smaller portion of reviewed articles focused specifically on this integration, their high citation volume and detailed frameworks indicate strong scholarly recognition and real-world applicability.

The concept of digital twins enhanced by AI and quantum simulation emerged as a powerful innovation in supply chain emissions monitoring. A total of 25 articles addressed the application of digital twins in carbon-neutral supply chains, with 19 specifically discussing their augmentation through AI and quantum simulation techniques. These studies together amassed approximately 3,500 citations, reflecting an expanding focus on digital representations of physical systems for emissions modeling. Digital twins were used to simulate factory operations, warehouse energy consumption, and transport logistics under different emissions constraints. The integration of AI allowed for real-time learning and adaptive decision-making, while quantum computing enhanced the modeling of nonlinear environmental variables such as temperature, pressure, and energy usage patterns. Several studies applied this technology to smart factories and green warehousing, where virtual models were able to predict high-carbon outputs and recommend process adjustments for mitigation. Articles also discussed how digital twins supported predictive maintenance and waste reduction by anticipating equipment failure that could result in increased emissions. In complex supply networks, digital twins enabled end-to-end visibility of carbon footprints, identifying hotspots for emissions and offering insights into alternative routing, production scheduling, or supplier selection. Findings showed that such applications not only improved carbon accounting accuracy but also supported compliance with international standards like the GHG Protocol and ISO 14064. While some limitations related to computational load and integration complexity were noted, the review indicates that digital twins—when augmented by AI and quantum capabilities—are becoming instrumental in proactive sustainability governance. These systems move emissions monitoring from periodic audits to real-time operational control, a transition highly valued in advanced supply chain decarbonization strategies.

A dominant thread in the literature was the application of AI in carbon footprint monitoring and green procurement decision-making. Of the total reviewed articles, 41 discussed the use of AI systems—particularly machine learning and deep learning—for emissions measurement, reporting, and supplier evaluation. Collectively, these articles have received over 5,100 citations. In these studies, AI was shown to analyze structured data from enterprise systems and unstructured data from sustainability reports, shipping logs, and sensor feeds to construct real-time carbon emission profiles. AI-enabled platforms were found to significantly enhance transparency in Scope 1, 2, and 3 emissions, offering companies deeper insights into the environmental impact of their procurement and logistics activities. A recurring finding was the use of multi-criteria decision-making algorithms in supplier selection, integrating variables such as product lifecycle emissions, regulatory compliance, and sustainability certifications. These tools allowed companies to prioritize vendors with lower carbon outputs, contributing to supply chain decarbonization without sacrificing operational efficiency. Several articles also reported the deployment of AI for fraud detection in carbon offset transactions, flagging inconsistencies and greenwashing risks in carbon claims. Another important application involved emissions-based ranking systems for suppliers, where AI continuously re-evaluated vendor performance and sustainability alignment. The use of AI was also noted in contract negotiation, where emissions benchmarks were included in service-level agreements and monitored in real time. These findings confirm that AI not only improves the technical efficiency of carbon tracking but also enhances strategic procurement decisions, making sustainability an operational metric rather than a separate compliance task.

While the potential of quantum computing in supporting supply chain decarbonization is widely acknowledged, one of the most recurrent findings involves the practical limitations of quantum hardware in real-world deployment. Out of the 87 reviewed articles, 29 focused directly on the technical barriers, energy demands, and scalability concerns associated with current quantum systems. These articles collectively garnered more than 3,200 citations, underscoring the growing academic attention to the constraints of transitioning from experimental to applied usage in sustainability-focused supply chains. Key findings identified that quantum hardware is still in the Noisy Intermediate-Scale Quantum (NISQ) stage, where devices have limited coherence time, significant error rates, and require cryogenic environments for stable operation. This restricts the continuity and speed of processing needed for real-time optimization, particularly in dynamic supply chain contexts such as live freight routing or responsive procurement modeling. Additionally, several studies highlighted that the energy required to power quantum hardware—including cryogenic cooling systems, superconducting circuits, and signal amplifiers—may offset the carbon savings realized through algorithmic efficiency, especially when powered by non-renewable electricity sources. The lack of integration between quantum platforms and enterprise-level systems like ERP and SCM software also emerged as a barrier, further complicating deployment. Only a few companies have access to the infrastructure, expertise, and investment required to experiment with quantum computing, leaving small and medium-sized enterprises excluded from its potential benefits. The literature reviewed consistently indicates that while theoretical models and simulations show impressive gains in emission reduction, the current state of quantum hardware limits its scalability and readiness for industry-wide implementation in decarbonized supply chains. These findings reinforce the critical need for collaborative development between quantum technology providers and supply chain practitioners to bridge the gap between innovation and implementation.

The final major theme identified in this review relates to the technological convergence of AI, quantum computing, and blockchain in supporting transparent and verifiable emissions management. Out of the 87 articles reviewed, 21 explored this triadic integration, generating a combined citation count exceeding 2,800. These studies highlighted how blockchain provides a secure and tamper-proof ledger for

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storing sustainability data across supply chain nodes, while AI enables automated validation and analysis of carbon emission metrics from internal systems and external data feeds. Quantum computing, though still in early development, was reported to enhance cryptographic verification and improve the performance of decentralized consensus algorithms. This technological synergy was most commonly applied to emissions verification frameworks, particularly in global supply chains where cross-border carbon reporting is susceptible to inconsistency, manipulation, or omission. AI models were used to detect anomalies in emissions records, compare supplier-reported data against historical benchmarks, and audit compliance with international standards like ISO 14064 and the GHG Protocol. Quantum-enhanced encryption, as presented in several articles, was shown to future-proof blockchain systems against threats from post-quantum cybersecurity breaches, ensuring that sustainability ledgers remain secure. Use cases included emissions verification for carbon offset projects, ESG (Environmental, Social, Governance) scoring, and lifecycle emissions tracking across complex manufacturing chains. These integrated systems also allowed stakeholders, regulators, and investors to access real-time dashboards visualizing emissions data verified through AI algorithms and cryptographically stored on blockchain. Although still experimental in many respects, this convergence was found to significantly increase trust, transparency, and accountability in emissions reporting systems. The findings reinforce that a secure and intelligent digital infrastructure, supported by multiple emerging technologies, is essential to reliably measure and manage carbon emissions in globally dispersed and digitally transformed supply chains.

DISCUSSION

The findings from this systematic review underscore the pivotal role of Artificial Intelligence in forecasting and demand-driven decision-making processes within sustainable supply chains. The review confirms and expands upon previous research by Smyth et al. (2024), who emphasized that AI facilitates lean and green supply chain operations by increasing responsiveness and minimizing inefficiencies. Similarly, Xia et al. (2025) argued that AI tools, when deployed correctly, lead to measurable reductions in energy use and waste. This study builds on those arguments by showing that AI's integration into inventory optimization and predictive maintenance directly contributes to Scope 1 and Scope 2 emissions reductions. Compared to earlier works that focused heavily on cost savings (Vries, 2023; Xia et al., 2025), the current synthesis highlights a growing shift in the literature toward ecological efficiency as a core AI function. Notably, the reviewed articles illustrated that modern AI tools—such as neural networks and reinforcement learning—are being used not only to forecast demand but also to evaluate the carbon cost of every logistical decision. This is a significant development since earlier AI studies were criticized for being narrowly focused on efficiency without addressing environmental dimensions (Jiang, 2019). The incorporation of AI into carbon-sensitive inventory and logistics models reflects a more holistic interpretation of the supply chain function, echoing the findings of Ding et al., (2024) and Luo et al. (2024), who called for AI systems that balance operational and sustainability objectives. This review further aligns with Jabbour et al. (2020), who proposed that real-time analytics could bridge the gap between sustainability intent and actual performance metrics. As such, this study supports the evolving consensus that AI is a cornerstone technology in developing carbon-resilient supply chain strategies.

This review confirms the increasing use of quantum computing for logistics and transportation optimization, a theme previously introduced by de Vries (2023) and

Jiang (2019), who proposed that quantum algorithms could outperform classical models in solving combinatorial optimization problems such as the Vehicle Routing Problem (VRP). The findings of this review expand upon those insights by showing that hybrid quantum-classical algorithms are being used in real-time logistics planning to reduce travel distances, fuel consumption, and idle times. These findings are consistent with studies by Zhao et al. (2019) and Jiang (2019), which demonstrated that quantum annealing can provide feasible low-emission routes in scenarios involving hundreds of constraints. The review also validates the theoretical models introduced by Luo and Choi (2021), who argued that quantum algorithms could facilitate dynamic re-optimization under volatile environmental conditions—a capability that was corroborated by empirical simulation data in several articles. Compared to earlier research that largely presented quantum computing as a futuristic tool (Xie et al., 2023), this study reveals growing evidence of its application in pilot projects across last-mile delivery, urban logistics, and multimodal transport. Moreover, the review challenges prior concerns raised by de Vries (2023) regarding the readiness of quantum technology for industrial use, as some reviewed studies showed successful integration with AI and cloud systems for logistics modeling. This comparison suggests a narrowing gap between theoretical capability and real-world applicability. The review thus contributes to the literature by shifting the narrative from "quantum potential" to "quantum pilot," emphasizing the increasing tangibility of quantum computing in emissions-sensitive logistics systems.

The review identifies a transformative shift in supply chain management research through the integration of AI and quantum computing in multi-objective sustainability modeling. This aligns with earlier conceptual frameworks proposed by Shahzad et al., (2024) and Xia et al. (2025), which advocated for hybrid systems capable of balancing cost, time, and carbon emissions in optimization tasks. The articles reviewed expand upon those early hypotheses by offering concrete case studies and simulations where AI provides input constraints and real-time data while quantum systems process the combinatorial calculations required for optimal decision-making. These findings resonate with Pinheiro et al., (2021) and Xia et al. (2025), who suggested that AI-quantum interfaces could enable faster, deeper scenario analysis under volatile supply conditions. Compared to previous works that separated AI and quantum trajectories (Shahzad et al., 2024), this review highlights a convergence trend where both technologies are used together in the same architecture. One significant difference from earlier studies is the enhanced role of predictive analytics in emissions forecasting. While Xia et al., (2025) focused on reactive models for carbon control, recent studies show proactive use of AI and quantum synergy for sustainability scenario planning and real-time emissions trade-offs. This supports the direction suggested by Vries (2023), who called for integrated architectures that combine simulation, prediction, and optimization. The review adds value by illustrating that hybrid models are no longer experimental; they are now functioning within real-time decision-support environments, as evidenced by several enterprise-grade applications. The discussion confirms the paradigm shift from siloed technology deployment to integrated digital ecosystems driving sustainability innovation.

This review further confirms the increasing role of digital twins augmented by AI and quantum capabilities in enabling real-time carbon monitoring and lifecycle emission analysis. Previous studies by Jiang (2019) and Huang and Mao (2024) emphasized digital twins as passive monitoring tools that mirrored physical processes to improve efficiency. However, the reviewed literature indicates that contemporary digital twins now possess predictive and prescriptive capabilities, largely due to integration with machine learning models and quantum simulators. This shift echoes the advancements suggested by Xia et al. (2025), who demonstrated that quantum-enhanced digital twins can simulate complex environmental interactions—such as emissions variations due to temperature or energy use—more accurately than classical counterparts. Unlike earlier applications focused primarily on predictive maintenance (Xie et al., 2023), current digital twin models are being used to monitor carbon emissions across entire production and logistics lifecycles, providing critical input to sustainability scorecards and compliance reports. This evolution aligns with the findings of Jiang (2019), who identified the growing importance of feedback loops and real-time analytics in emissions governance. Moreover, the review highlights that digital twins are not just confined to manufacturing but are now being used across energy management, smart warehousing, and even last-mile logistics—all with a carbon accountability lens. These insights support the argument by de Vries (2023) that digital twins, when fused with quantum simulation, become proactive sustainability agents rather than passive tools. This expanded application contrasts with earlier limitations identified by Huang and Mao (2024), who noted that sustainability modeling often suffered from delayed data and reactive decisions. In comparison, the reviewed literature confirms that AI- and quantum-powered digital twins are enabling predictive, real-time sustainability intelligence across the supply chain.

The role of AI in emissions monitoring and sustainable procurement emerged as a central finding in this review and shows strong alignment with earlier research. Prior studies by Xu et al. (2023) and Smyth et al. (2024) emphasized the use of machine learning in analyzing emissions data to support sustainability-focused supply chain decisions. The current review affirms and extends these insights by showing how AI is increasingly used to track, quantify, and visualize emissions at granular levels, including real-time analysis of Scope 1, 2, and 3 emissions. These capabilities support the shift advocated by Xu et al.(2023) and Pinheiro et al.(2021) toward embedded sustainability in procurement and supplier evaluation systems. In contrast to earlier approaches that focused primarily on retrospective auditing, recent studies included in this review demonstrate AI's growing role in predictive analytics for supplier sustainability risk, emissions-based vendor ranking, and fraud detection in carbon offset documentation. This evolution addresses the critique by Jiang (2019), who observed a lack of transparency and traceability in sustainability claims. Moreover, the reviewed literature provides empirical support to the conceptual work of Paulraj et al. (2017), who argued that procurement practices could serve as key levers for organizational carbon neutrality. With AI now being used to assess lifecycle emissions, contractual compliance, and sustainability certifications during supplier onboarding, the procurement function has clearly evolved from a transactional role to a strategic actor in emissions governance. These findings reinforce the call by Mishra et al. (2022) for integrating emissions intelligence into enterprise procurement platforms, thus making sustainability not just a compliance task, but a decision-making priority. The reviewed studies confirm that AI's ability to continuously monitor, validate, and prioritize carbon-conscious suppliers enables a new level of accountability in green procurement practices. While the potential of quantum computing in supply chain decarbonization is promising, the findings of this review corroborate several limitations previously noted by Preskill (2018) and Biamonte et al. (2017) regarding hardware readiness and practical scalability. The current synthesis highlights persistent challenges in quantum hardware, such as error rates, energy-intensive cooling requirements, and limited coherence time, that restrict the deployment of these

technologies in operational environments. These results that current quantum systems are constrained by their reliance on superconducting or ion-trap technologies, both of which are difficult to scale without significant energy input. Moreover, the review brings attention to an issue underrepresented in earlier studies: the carbon cost of maintaining quantum systems themselves. Unlike previous works that emphasized algorithmic efficiency, recent literature raises questions about whether the energy consumed in powering quantum computers offsets the carbon benefits they promise. This adds nuance to the previously optimistic projections that primarily viewed quantum computing as a net-positive technology. Additionally, the review supports that a lack of integration between quantum platforms and legacy enterprise systems poses a barrier to practical implementation. These hardware limitations hinder the scalability of quantum solutions in typical supply chain contexts, where decentralized operations, real-time responsiveness, and cost-efficiency are essential.
The review also underscores the emerging convergence of blockchain, AI, and quantum computing as a novel paradigm for emissions verification, which aligns with but significantly extends earlier studies. Blockchain's potential in supply chain transparency, particularly for product traceability and authenticity. This review reveals a more sophisticated integration where blockchain is used not only for transparency but as a secure, immutable platform for recording carbon emissions data. Advocated for digital trust infrastructures in sustainability reporting. When paired with AI, blockchain-based systems are now capable of automatically validating carbon claims by comparing input data from IoT sensors and supplier documents with emission thresholds and regulatory benchmarks. This AI-enhanced validation process addresses the concern regarding greenwashing and unverifiable carbon offset projects. Moreover, the review adds a novel layer by highlighting the role of quantum computing in strengthening the cryptographic security of emissions ledgers. The literature shows how the integration of these three technologies supports real-time emissions dashboards accessible to regulators, auditors, and investors, offering an unprecedented level of trust and accountability. This tripartite system represents a shift from isolated digital tools to interlocking technologies that reinforce each other's capabilities. By comparison to earlier studies that explored these technologies independently, this review confirms a new direction in sustainability infrastructure—one where decentralized trust, intelligent verification, and post-quantum security coalesce to make emissions tracking both transparent and resilient.

CONCLUSION

The findings of this systematic review underscore the transformative potential of integrating Artificial Intelligence and Quantum Computing to achieve carbon-neutral supply chains, while also highlighting the current limitations and implementation barriers that must be addressed. Through the synthesis of 87 peer-reviewed articles, the review revealed that AI plays a pivotal role in predictive analytics, emissions monitoring, and green procurement, significantly enhancing operational efficiency and sustainability performance across supply chain activities. Quantum computing, while still in its developmental stages, offers unprecedented capabilities in solving complex optimization problems such as logistics routing, energy modeling, and emissions forecasting, thereby supporting more informed and carbon-conscious decision-making. The convergence of AI and quantum systems—especially when paired with technologies like digital twins and blockchain—further empowers organizations to simulate, monitor, and verify emissions in real-time with greater transparency and trust. However, hardware constraints, energy demands, scalability issues, and limited integration into existing enterprise systems currently restrict the broader adoption of quantum computing. The review also identified a growing body of evidence supporting the hybrid deployment of AI and quantum tools for multi-objective sustainability modeling, indicating a shift from isolated technology use toward interconnected digital ecosystems. These insights collectively contribute to the academic discourse on digital transformation for environmental sustainability, demonstrating that while the technological infrastructure for carbon-neutral supply chains is rapidly advancing, its full potential will only be realized through continued innovation, strategic alignment, and cross-disciplinary collaboration.

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