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Article

QUANTUM AI-DRIVEN BUSINESS INTELLIGENCE FOR CARBON-NEUTRAL SUPPLY CHAINS: REAL-TIME PREDICTIVE ANALYTICS AND AUTONOMOUS DECISION-MAKING IN COMPLEX ENTERPRISES.

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ABSTRACT

Amid growing global pressures to combat climate change, enterprises are reengineering their supply chains to align with carbon-neutral objectives while maintaining operational agility and competitiveness. This study explores the transformative potential of integrating Quantum Artificial Intelligence (QAI), Business Intelligence (BI), and autonomous decision-making technologies in building intelligent, sustainable supply chains capable of minimizing environmental impact. By leveraging the computational advantages of quantum algorithms, machine learning, real-time analytics, and decentralized control systems, organizations can address the increasing complexity of emissions management, logistics optimization, and sustainability forecasting. A comprehensive systematic literature review was conducted following the PRISMA 2020 guidelines, encompassing 97 peer-reviewed articles published between 2010 and 2024 across fields including supply chain management, artificial intelligence, quantum computing, and sustainability analytics. The review reveals that QAI significantly enhances the efficiency of solving combinatorial problems such as routing, scheduling, and emissions prediction, outperforming classical AI in both speed and scalability. BI platforms have evolved from retrospective reporting tools to intelligent systems that facilitate real-time carbon monitoring, dynamic scenario modeling, and sustainability-focused KPI visualization. In parallel, the deployment of autonomous systems—supported by IoT, RFID, edge computing, and AI agents—has enabled decentralized, self-optimizing decision-making across manufacturing, logistics, and procurement functions. Real-world case studies from industry leaders like Siemens, IBM, Honeywell, and John Deere illustrate the tangible impact of these technologies in achieving emissions reductions and improving system-wide sustainability performance. This study provides a comprehensive understanding of how the convergence of QAI, BI, and autonomous systems is shaping the future of carbon-conscious supply chains, offering both theoretical advancement and practical relevance for businesses committed to environmental responsibility and technological innovation.

KEYWORDS

Quantum AI; Carbon Neutrality; Predictive Analytics; Autonomous Decisions; Business Intelligence;

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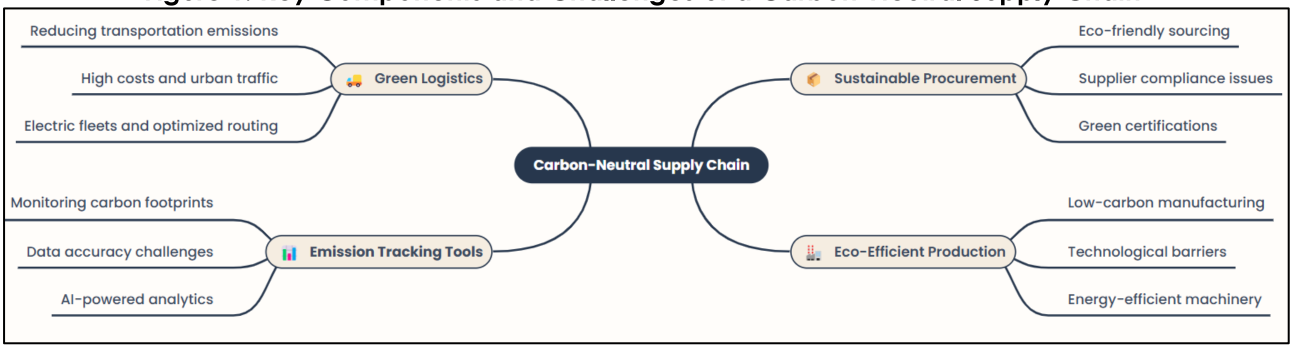
INTRODUCTION

The transition toward carbon-neutral supply chains has emerged as a central goal for enterprises responding to environmental sustainability mandates and international climate accords such as the Paris Agreement (Saberi et al., 2018). Carbon-neutrality refers to achieving net-zero carbon emissions by balancing emitted and offset carbon, a complex task when scaled across global, multi-tier supply chains (Cong et al., 2024). Organizations such as Unilever, IKEA, and Amazon have committed to reducing their supply chain carbon footprints through innovations in green logistics, eco-efficient production, and sustainable procurement. However, this endeavor is often hindered by the lack of intelligent systems capable of offering real-time insights and predictive capabilities across heterogeneous supply chain nodes (Pan et al., 2019; Zhang et al., 2021). Enterprises must reconcile operational efficiency with emission targets, requiring a fundamental redesign of business intelligence systems to include autonomous and high-speed decision-making processes enabled by next-generation technologies (Huang et al., 2009; Lewandowski, 2017). Moreover, Quantum Artificial Intelligence (QAI) has surfaced as a promising innovation to address these challenges by enhancing the computational depth and learning capacity of traditional AI models. By integrating quantum computing principles—such as superposition and entanglement—into machine learning algorithms, QAI can process vast datasets and compute multiple possibilities simultaneously (Chen, 2021; Downie & Stubbs, 2012). For example, Volkswagen has experimented with quantum algorithms for traffic flow optimization in urban logistics, which can directly reduce CO_2 emissions from delivery fleets (Jabbour et al., 2018). Similarly, D-Wave Systems collaborated with Save-On-Foods to implement quantum machine learning in optimizing refrigerated supply chain routes, reducing fuel consumption and spoilage (Pinkse & Busch, 2013). These case studies underscore the ability of QAI to manage complex, variable-rich supply chain environments that traditional algorithms often struggle with.

Figure 1: Key Components and Challenges of a Carbon-Neutral Supply Chain



In parallel, the evolution of Business Intelligence (BI) from static reporting tools to dynamic, AI-augmented platforms has enabled decision-makers to monitor, analyze, and act on data more proactively (Alijoyo et al., 2024). Conventional BI systems often rely on batch data and predefined KPIs, limiting their relevance in fast-paced supply chain contexts. For instance, a global retailer like Walmart requires instantaneous analytics for inventory management, demand prediction, and warehouse emissions monitoring (Danish & Senjyu, 2023). AI-enhanced BI systems can automate pattern detection in energy use, carbon emissions, and procurement cycles (Alijoyo et al., 2024). When layered with quantum-enhanced computation, such systems gain the capacity to process multi-dimensional data sets in near real-time, enabling businesses to preemptively identify carbon hotspots, predict the environmental impact of routing decisions, and rebalance operations accordingly (Alijoyo et al., 2024; Cong et al., 2024; Tosun, 2022). Moreover, eal-time predictive analytics serve as the cornerstone of carbon-neutral supply chain intelligence. These analytics forecast demand fluctuations, shipping delays, and production anomalies, allowing firms to make adjustments that reduce carbon output without compromising service quality (Danish, 2023; Rojek et al., 2023). For example, UPS uses dynamic routing systems to reduce mileage and idle time, which contributes to both lower emissions and operational cost savings (Danish & Senjyu, 2023). Additionally, Procter & Gamble has adopted AI-based forecasting to optimize energy usage in its manufacturing plants, aligning electricity demand with peak renewable energy availability (Fehr &

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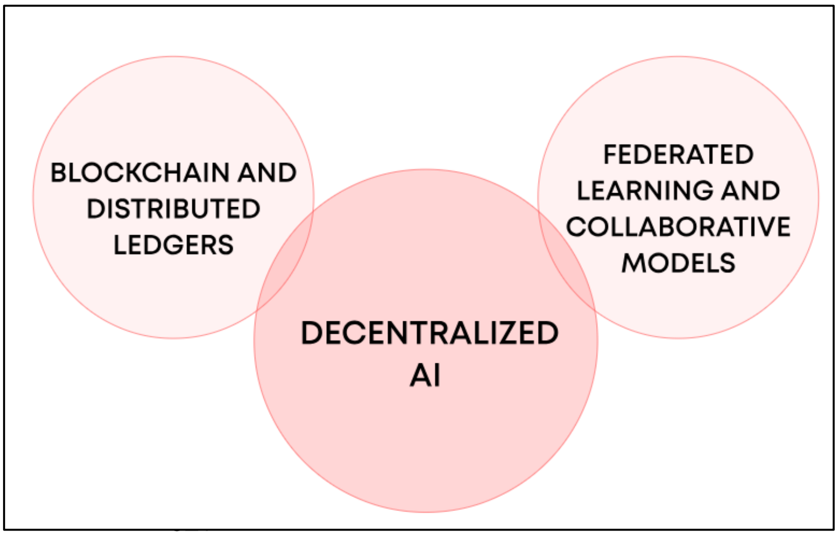
Gächter, 2002). Quantum AI further amplifies these benefits by enabling faster and more nuanced predictions—such as simulating multiple emission scenarios or identifying non-obvious correlations between supplier behavior and carbon intensity (Cong et al., 2024; Fehr & Gächter, 2002).
Autonomous decision-making, an essential feature of smart supply chains, refers to systems capable of independently executing tasks such as rerouting shipments, adjusting production plans, or renegotiating contracts based on environmental and economic inputs (Tosun, 2022). Enterprises like Siemens and General Electric have started integrating digital twins and AI agents that autonomously adapt supply chain parameters in response to energy consumption or carbon emission thresholds (Pan et al., 2019). In agriculture, John Deere has utilized AI-driven tractors to optimize seeding paths and fertilizer usage, significantly lowering greenhouse gas emissions in supply chains linked to food production (Li et al., 2019). Quantum AI enables these autonomous systems to execute decisions faster and more accurately by rapidly solving complex optimization problems such as the Traveling Salesman Problem or multi-modal transport scheduling (Chen et al., 2022; Li et al., 2019).
The complexity of today's supply chains—marked by global supplier diversity, volatile demand cycles, and geopolitical uncertainties—calls for decentralized and adaptive intelligence mechanisms (Manupati et al., 2019). Centralized decision-making systems are often too rigid and delayed to manage carbon-neutrality targets at the micro-operational level. Quantum AI-driven BI platforms can embed decision-making logic at various supply chain nodes, such as factories, distribution centers, or logistics hubs, allowing them to self-optimize operations based on localized data (Lee et al., 2014; Matthews et al., 2008). For instance, Maersk has piloted blockchain and AI-integrated systems to allow port-level adjustments in shipping schedules to reduce idle time and emissions (Zhang et al., 2022). Such distributed intelligence is made computationally viable with quantum capabilities, which support high-volume processing of interdependent data from sensors, satellites, and enterprise systems. Moreover, the ability to model, forecast, and respond to carbon-related variables in real time offers operational and regulatory advantages. Predictive models trained on historical emissions data can detect patterns related to specific suppliers, transportation methods, or packaging materials (Lee et al., 2014; Li et al., 2019). Companies such as Tesla use AI to track supply chain emissions from mining operations to battery assembly, ensuring transparency and accuracy in their sustainability reports (Koh et al., 2013). With quantum-enhanced analytics, these models can consider higher-order variables and run large-scale simulations in compressed timeframes, aiding in compliance with global environmental standards such as ISO 14001 or the EU Green Deal (Manupati et al., 2019; Zhang et al., 2022). This predictive edge enhances responsiveness to carbon tax regimes and emission trading systems, which are becoming increasingly common across international markets.
The integration of Quantum AI, BI systems, and predictive analytics forms a synergistic foundation for carbon-neutral supply chain management. Real-world implementations by companies like DHL, PepsiCo, and Nestlé demonstrate how AI-powered platforms are reshaping sustainability strategies by tracking carbon data across the supply chain lifecycle (Gong et al., 2018; Jaber et al., 2013). These companies have implemented dashboards powered by AI to analyze transportation footprints, production emissions, and vendor sustainability

Figure 2: Building Blocks of Decentralized AI Systems



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compliance. Quantum-enhanced models, when embedded into such platforms, elevate these capabilities from reactive reporting to proactive orchestration, enabling organizations to operate resilient and sustainable supply chains across volatile and competitive global markets (Jia et al., 2019; Wang et al., 2019). The convergence of these technologies supports smarter, leaner, and greener supply chains across industries including automotive, pharmaceuticals, electronics, and fast-moving consumer goods.The primary objective of this study is to examine how the integration of Quantum Artificial Intelligence (QAI) with Business Intelligence (BI) systems can facilitate the development and operation of carbon-neutral supply chains. Specifically, the study seeks to analyze the role of QAI in enhancing real-time predictive analytics, enabling autonomous decision-making, and optimizing data-driven strategies for emissions reduction across complex enterprise networks. By exploring empirical evidence, real-world applications, and theoretical models, the study aims to establish a comprehensive framework that demonstrates how QAI-powered BI tools can support supply chain sustainability through improved data processing, dynamic forecasting, and operational efficiency. Additionally, this research intends to evaluate the computational advantages of quantum-enhanced algorithms in solving logistical, environmental, and managerial challenges that conventional AI and classical BI systems face when pursuing carbon neutrality goals.

LITERATURE REVIEW

The increasing complexity of global supply chains and the mounting pressure for environmental accountability have necessitated a shift toward carbon-neutral operational models. In this context, academic and industrial research has intensified on how advanced technologies such as Artificial Intelligence (AI), Quantum Computing (QC), and Business Intelligence (BI) can drive sustainable transformation in supply chains. The literature reflects a growing consensus that traditional BI systems, although useful for descriptive analytics, fall short when addressing the real-time demands and predictive complexities of carbon-neutral logistics. Simultaneously, the emergence of Quantum AI (QAI)—a fusion of quantum computing and machine learning—offers a promising avenue for solving optimization problems that are computationally infeasible for classical systems. This review synthesizes foundational and recent contributions across several interconnected domains, including carbon-neutral supply chain practices, AI-enhanced BI systems, quantum computing applications, and real-time predictive analytics. The goal is to establish a theoretical and practical understanding of how these technologies intersect and contribute to autonomous, environmentally conscious supply chain decision-making. This literature review is organized into six distinct but interrelated subsections, each addressing a critical aspect of the study's conceptual foundation.

Carbon Neutrality in Supply Chain Management

Carbon neutrality in supply chains refers to the process by which organizations reduce greenhouse gas (GHG) emissions across the entire value chain and compensate for residual emissions through carbon offsetting or sequestration initiatives (Zhang et al., 2022). In logistics and manufacturing contexts, carbon neutrality involves minimizing direct emissions from production (Scope 1), indirect emissions from purchased energy (Scope 2), and all other indirect emissions associated with outsourced operations and end-product usage (Scope 3) (Zhang et al., 2021). Operationalization of this concept requires embedding emission tracking into the supply chain through data-driven tools such as carbon accounting software, Internet of Things (IoT) sensors, and AI-based analytics platforms (Pinkse & Busch, 2013). Firms like IKEA and Apple have implemented internal carbon pricing mechanisms and renewable energy procurement strategies to move toward operational neutrality
(Chen et al., 2022). However, the decentralized nature of global supply chains complicates carbon neutrality efforts, especially when suppliers and logistics providers operate in jurisdictions with varying emission standards (Pinkse & Busch, 2013).

Carbon neutrality strategies must address industry-specific challenges. In the manufacturing sector, emission hotspots include raw material extraction, energy-intensive production processes, and end-of-life product disposal (Zhang et al., 2022). Green manufacturing practices, including eco-design, closed-loop production, and energy efficiency improvements, play vital roles in achieving carbon

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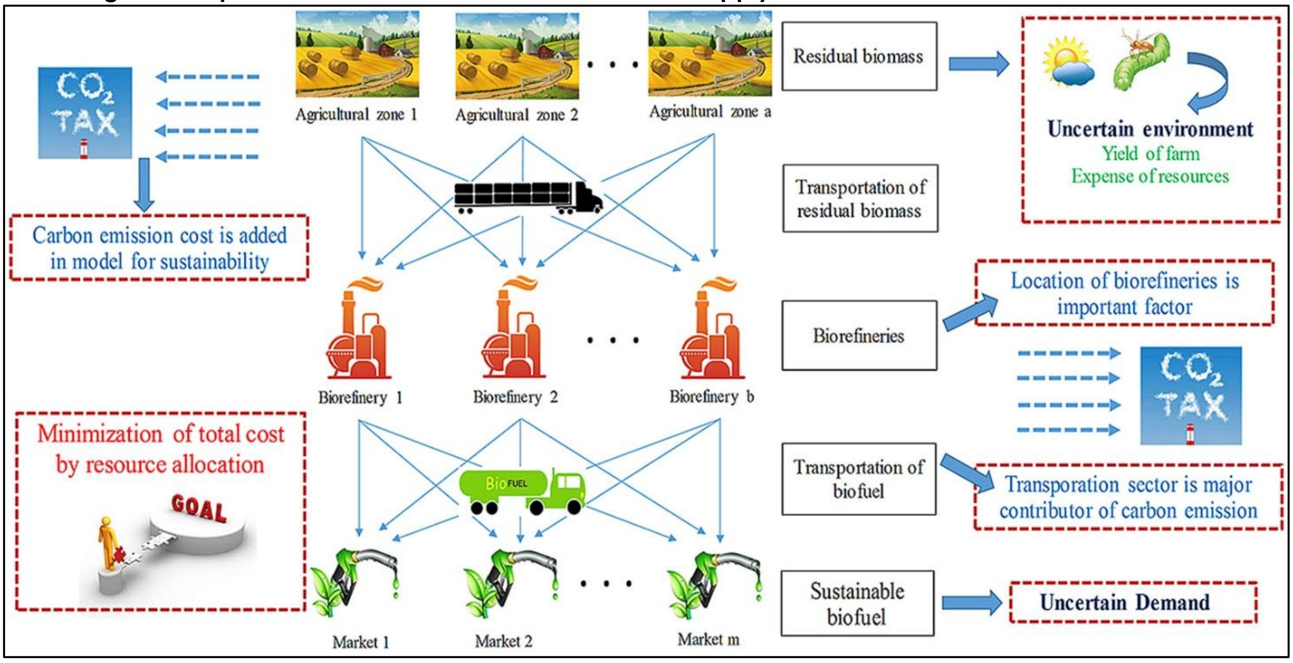
neutrality (Chen, 2021). In logistics, freight transportation is a key contributor to GHG emissions, prompting adoption of route optimization, modal shifts from road to rail, and electrification of vehicle fleets (Chen, 2021; Lewandowski, 2017). Companies such as DHL and FedEx have adopted carbon-neutral shipping options by incorporating biofuels and offset programs into their logistics strategies (Downie & Stubbs, 2012; Lemma et al., 2021). Nonetheless, the measurement and verification of emissions remain a challenge, particularly in multi-tier supply chains with opaque supplier practices (Chen, 2021).

Figure 3: Impact of carbon emission in a sustainable supply chain for Second Generation Biofuel



Source: Ahmed and Sarkar *(2018)*

Global policy instruments are driving the adoption of carbon-neutrality in supply chains. The Paris Agreement, adopted in 2015 under the United Nations Framework Convention on Climate Change (UNFCCC), committed participating countries to limit global warming to well below 2°C, encouraging national policies that incentivize low-carbon supply chain transformations (Tosun, 2022). In response, countries and regions have introduced environmental regulations and reporting frameworks. The European Union's Green Deal promotes carbon-neutral industry practices by 2050 and includes mechanisms like the Carbon Border Adjustment Mechanism (CBAM), which places tariffs on carbon-intensive imports to prevent "carbon leakage" (Waichman et al., 2021). Such regulations create competitive pressure for global firms to decarbonize upstream and downstream operations (Barrett & Dannenberg, 2012; Nordhaus, 2019). Similarly, frameworks like ISO 14064 and the Greenhouse Gas Protocol provide standardized methodologies for measuring and reporting supply chain emissions (Cronin et al., 2018; Lewandowski, 2017).

Multinational corporations have increasingly aligned their sustainability strategies with global policy directives, driven not only by compliance but also by market and investor expectations (Lemma et al., 2021). Firms such as Nestlé and Unilever have committed to science-based targets and have adopted supplier engagement programs to monitor emissions at every supply chain tier (Barrett & Dannenberg, 2012). These commitments often involve the use of digital technologies for carbon data collection and analysis, such as blockchain for traceability, cloud-based emissions dashboards, and predictive models for carbon footprint estimation (Pan et al., 2019). Furthermore, investor-led initiatives like the Task Force on Climate-related Financial Disclosures (TCFD) and Climate Action 100+ have added pressure on enterprises to make climate risk and emissions visible across all business operations, including procurement and logistics (Chen, 2021; Dorokhova et al., 2021). Achieving carbon neutrality in supply chains also intersects with national industrial policies and regional trade agreements. Countries such as Germany and Japan have implemented green

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industrial strategies that provide tax incentives and subsidies for adopting low-carbon technologies in supply chains (Cronin et al., 2018; Lewandowski, 2017). Regional agreements like the ASEAN Action Plan on Energy Cooperation encourage member states to harmonize sustainability reporting and adopt renewable energy in cross-border logistics (Zhang et al., 2022). In addition, consumer-facing eco-labeling systems—such as Carbon Trust's Product Footprint Certification or Amazon's Climate Pledge Friendly—encourage companies to enhance transparency on product-related emissions (Lewandowski, 2017; Zhang et al., 2022). These developments emphasize how the operationalization of carbon neutrality in supply chains is influenced not just by firm-level initiatives but also by an evolving global policy ecosystem that integrates regulatory, market-based, and voluntary instruments (Hua et al., 2020).

Role of Scope 1, 2, and 3 emissions in supply chain footprint

Supply chain emissions are categorized into three distinct scopes, as defined by the Greenhouse Gas Protocol, each representing different sources of carbon output and operational boundaries. Scope 1 refers to direct emissions from owned or controlled sources such as company vehicles or on-site fuel combustion (Sharma et al., 2020). Scope 2 includes indirect emissions from purchased electricity, steam, heating, and cooling consumed by the reporting company (Huang et al., 2009). Scope 3 covers all other indirect emissions that occur in a company's value chain, including upstream and downstream activities such as raw material extraction, transportation, product use, and disposal (Lewandowski, 2017). While Scopes 1 and 2 are often under a firm's direct control, Scope 3 emissions represent the most substantial and challenging component of a company's carbon footprint, often accounting for over 70% of total emissions in manufacturing and retail supply chains (Downie & Stubbs, 2012). Accurately quantifying and managing Scope 3 emissions has become critical for organizations striving toward carbon neutrality, as these emissions encompass supplier activities, logistics operations, and consumer end-use patterns (Zhang et al., 2021). For instance, in the apparel and electronics industries, emissions related to product use and disposal can exceed production-related emissions (Cronin et al., 2018; Jaeger et al., 2022). According to the Science Based Targets initiative (SBTi), companies must account for Scope 3 emissions to validate their net-zero strategies (Downie & Stubbs, 2012). However, transparency issues, lack of real-time data, and supplier engagement barriers hinder comprehensive Scope 3 monitoring (Danish & Senjyu, 2023). Firms are increasingly investing in AI-driven analytics, life cycle assessment (LCA) tools, and blockchain-based traceability platforms to capture emissions across fragmented supply chain layers (Lee, 2011).Walmart's Project Gigaton is one of the most prominent corporate initiatives targeting Scope 3 emissions at scale. Launched in 2017, the project aims to avoid one billion metric tons (a gigaton) of greenhouse gases from Walmart's global value chain by 2030. It encourages suppliers to set reduction targets in six key areas: energy, agriculture, waste, packaging, transportation, and product use (CDP, 2020). Walmart employs digital dashboards and supplier reporting tools to aggregate data and monitor progress toward emissions reductions, reflecting the operationalization of Scope 3 management through integrated Business Intelligence systems (Zhang et al., 2021). The project not only enhances Walmart's environmental performance but also pressures upstream suppliers to adopt sustainability metrics, making emissions management a collective supply chain responsibility (Lee, 2011).

IKEA's zero-emission logistics goals provide another practical illustration of integrating Scope 1 and 2 reductions within supply chain strategy. The company has pledged to use 100% zero-emission delivery vehicles in key cities and transition to renewable energy in its operations by 2030. IKEA's Scope 1 strategies include switching to electric fleets and improving last-mile delivery systems, while Scope 2 efforts focus on installing rooftop solar panels and sourcing electricity from renewable providers across warehouses and stores (Bao et al., 2021; Chandel et al., 2023). The company also engages in supplier audits and collaborates with transport providers to enhance the sustainability of logistics operations (Cronin et al., 2018; Parag & Sovacool, 2016). This demonstrates how global firms are actively integrating emission reductions at various operational levels, supported by emissions data platforms and sustainability KPIs that inform real-time decision-making. Several multinational firms have followed suit, setting science-based targets that include all three emission scopes to comply with emerging regulatory frameworks such as the EU's Corporate Sustainability

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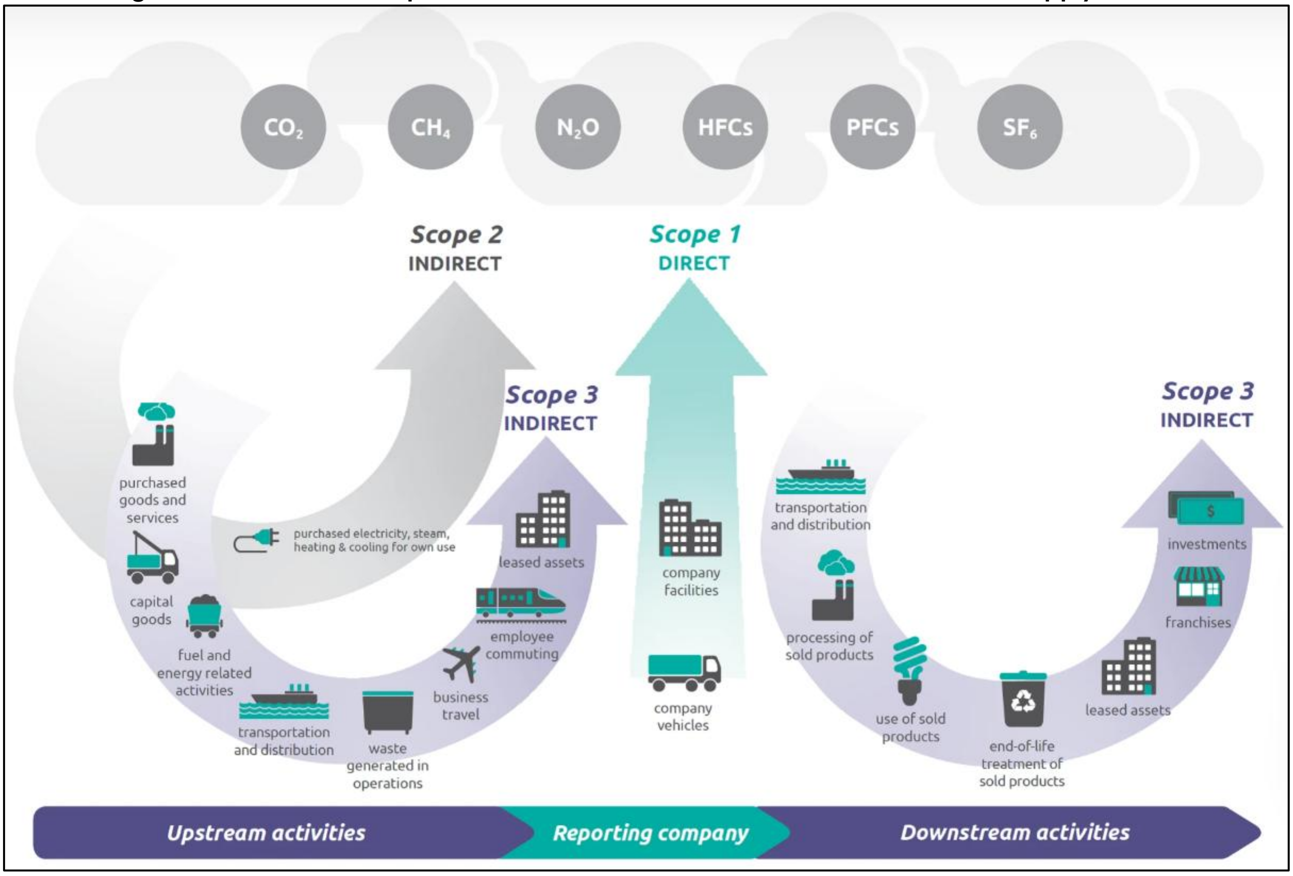
Reporting Directive (CSRD) and the U.S. Securities and Exchange Commission's (SEC) proposed climate disclosures (Carmichael & Liao, 2022; Devaraj et al., 2021). Amazon's Climate Pledge Friendly program and Microsoft's carbon fee model exemplify how companies monetize internal carbon emissions to drive change across departments and suppliers (Ahmad et al., 2021; Xiao et al., 2018). These examples highlight that comprehensive carbon neutrality requires an integrated strategy across Scope 1, 2, and 3, supported by digital infrastructure, supplier collaboration, and policy alignment (Parag & Sovacool, 2016; Tajjour & Chandel, 2023). The complexity of managing this emission triad reinforces the importance of robust data systems, real-time analytics, and predictive modeling in transforming global supply chains into carbon-neutral ecosystems.

Figure 4: Overview of Scope 1, 2, and 3 Greenhouse Gas Emissions Across the Supply Chain



Source: www.soletairpower.fi (2024)

Business Intelligence for Sustainable Operations

Business Intelligence (BI) has evolved significantly over the past two decades, transitioning from static, retrospective reporting tools to dynamic, real-time systems integrated with artificial intelligence (AI) and big data technologies (Alijoyo et al., 2024). Early BI systems primarily focused on descriptive analytics, offering static dashboards, periodic performance reports, and manually generated summaries (Zhu & Yu, 2023). These tools provided limited insights into sustainability because they lacked the speed, granularity, and adaptability required for managing emissions or energy use in volatile supply chain environments (Brown & Kroll, 2017; Mengelkamp et al., 2017). The increasing availability of data streams from IoT sensors, RFID tags, and cloud-based ERP systems has enabled the rise of intelligent BI platforms that deliver real-time monitoring and adaptive analytics for green operations (Fombrun & Foss, 2004; Sharma et al., 2020; Zhu & Yu, 2023). Modern BI systems integrate predictive and prescriptive analytics to allow businesses to simulate sustainability scenarios, evaluate trade-offs, and make informed carbon-sensitive decisions (Dwivedi et al., 2021; Sharma et al., 2020).

Real-time, AI-integrated BI systems provide a significant advantage in operationalizing sustainability across supply chains. These systems ingest high-frequency data related to logistics, manufacturing,

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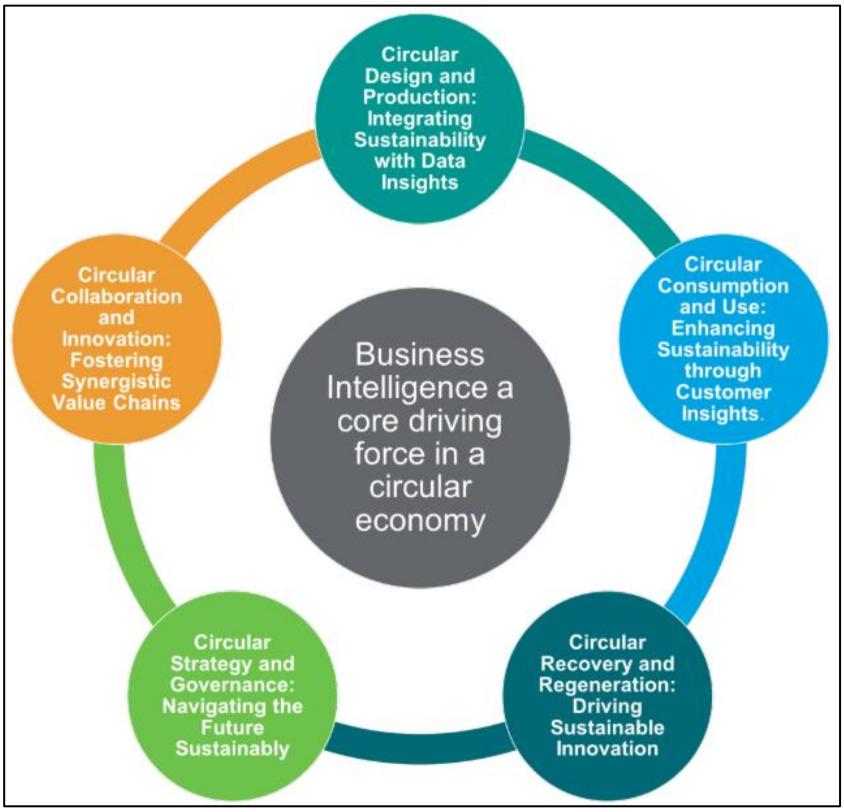
procurement, and customer behavior to detect inefficiencies that contribute to environmental degradation (Alijoyo et al., 2024; Brown & Kroll, 2017). For example, predictive algorithms can anticipate machine downtimes or overproduction events that lead to increased energy use or waste (Christidis & Devetsikiotis, 2016; Dorokhova et al., 2021). Coca-Cola has adopted BI tools connected to smart meters and IoT-enabled facilities to monitor water consumption and energy efficiency in real time (Cronin et al., 2018). Similarly, Schneider Electric uses advanced BI platforms to track and reduce energy consumption across global manufacturing sites, integrating sustainability metrics directly into its production workflows (Fombrun & Foss, 2004; Sharma et al., 2020). These case studies highlight how organizations embed intelligence at various levels of the supply chain to enable proactive emissions management.

Figure 5: Business Intelligence a core driving force in a circular economy



The architecture of modern BI systems supporting sustainability initiatives is characterized by several key components: data lakes, AI-powered analytics engines, visualization layers, and APIs for cross-platform integration (Cronin et al., 2018; Zhu & Yu, 2023). These platforms consolidate data from multiple sources—including ERP, SCM, CRM, and IoT devices—into centralized cloud infrastructures that support scalability and real-time analytics (Dwivedi et al., 2021; Zhu & Yu, 2023). Microsoft's Power BI and SAP Analytics Cloud, for instance, enable real-time emissions dashboards and supplier risk maps that help sustainability managers make data-driven decisions (Juszczyk & Shahzad, 2022; Mengelkamp et al., 2017). Additionally, AI modules within BI platforms enhance forecasting accuracy for emissions, fuel consumption, and transportation delays—variables critical to carbon-neutral goals (Sharma et al., 2020; Zhu & Yu, 2023). Through machine learning and anomaly detection, these systems flag deviations from sustainability benchmarks, helping companies intervene early and avoid environmental penalties or inefficiencies (Burton-Chellew et al., 2013; Zhang et al., 2022).

Supply chain sustainability is inherently cross-functional, requiring seamless coordination between procurement, logistics, operations, and compliance teams. BI systems facilitate this coordination through shared dashboards, role-based data access, and customizable KPI tracking (Ahmad et al., 2021; Ford & Hardy, 2020). For instance, Walmart uses a custom BI platform under Project Gigaton to aggregate supplier data and monitor emissions across product categories, enabling data visibility and supplier accountability (Andoni et al., 2019; Brown & Kroll, 2017). At Unilever, real-time BI dashboards are integrated into supply chain control towers to track product carbon footprints, transportation emissions, and sourcing-related deforestation risks (Fombrun & Foss, 2004; Zhu & Yu, 2023). These implementations show that BI tools do more than report—they support dynamic decision-making and foster collaboration across extended supply networks. As the pressure for transparency and accountability increases from both regulators and consumers, BI systems are becoming essential infrastructure for sustainability. They provide the analytical backbone required for corporate climate disclosures, compliance with ESG (Environmental, Social, Governance) frameworks, and participation in voluntary carbon markets (Brown & Kroll, 2017; Mengelkamp et al.,

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2017). Moreover, BI platforms help companies align with regulatory frameworks such as the EU Corporate Sustainability Reporting Directive (CSRD) and the U.S. SEC climate disclosure guidelines by automating the tracking and reporting of emissions-related KPIs (Cronin et al., 2018). The confluence of real-time data processing, AI-driven analysis, and visual storytelling empowers enterprises to transform BI systems into sustainability intelligence centers that inform, guide, and validate carbon-reduction strategies at every level of the supply chain.

Business Intelligence for Emissions and Sustainability Monitoring

Business Intelligence (BI) tools have become instrumental in enabling organizations to monitor emissions across multiple levels of their supply chain. Emissions monitoring, once a static and retrospective process, has shifted to a real-time, data-driven function with the incorporation of cloud computing, AI, and IoT-enabled sensors (Alijoyo et al., 2024; Zhu & Yu, 2023). These BI systems continuously collect data on fuel consumption, energy usage, transportation emissions, and waste outputs to provide timely insights into environmental performance (Fombrun & Foss, 2004; Sharma et al., 2020). For instance, Coca-Cola utilizes IoT-connected water meters and centralized BI platforms to track water use per product unit, helping reduce overconsumption and meet water replenishment targets. Such real-time BI applications are particularly relevant for complex supply chains operating in diverse regulatory environments, where centralized emissions tracking and visualization allow for coordinated sustainability initiatives across business units (Dorokhova et al., 2021; Zhu & Yu, 2023).Supplier sustainability assessment is another critical area where BI plays a transformative role. Organizations depend heavily on upstream partners for materials, transportation, and energy-intensive processes, making supplier practices central to overall carbon footprints (Andoni et al., 2019). BI platforms integrated with procurement and vendor databases allow sustainability managers to evaluate supplier performance using environmental, social, and governance (ESG) metrics (Fombrun & Foss, 2004; Ford & Hardy, 2020; Sharma et al., 2020). Tools such as supplier scorecards and emissions dashboards visualize each vendor's contribution to Scope 3 emissions, facilitating more sustainable sourcing decisions (Christidis & Devetsikiotis, 2016; Cruzes et al., 2014). For example, Unilever's Sustainable Living Plan uses BI dashboards to monitor supplier compliance with greenhouse gas reduction goals and to track progress toward deforestation-free supply chains (Brown & Kroll, 2017; Burton-Chellew et al., 2013). This data-driven approach enables continuous evaluation and fosters collaboration with suppliers on sustainability performance improvement.

KPI visualization is a core function of BI systems that facilitates transparency, accountability, and strategic alignment. Environmental KPIs—such as CO_2 per unit shipped, percentage of recycled input materials, or energy consumption per unit produced—are now tracked alongside traditional financial metrics (Andoni et al., 2019; Ford & Hardy, 2020). Real-time dashboards offer cross-functional visibility into sustainability progress, allowing supply chain managers, compliance officers, and C-suite executives to make aligned decisions (Ahmad et al., 2021; Cruzes et al., 2014). Microsoft Power BI, in Coca-Cola's sustainability program, visualizes plant-level water usage efficiency, carbon intensity trends, and regional differences in consumption patterns (Cronin et al., 2018). This visualization enables dynamic benchmarking and regional strategy differentiation, ensuring that operations remain aligned with global sustainability targets without compromising local adaptability (Burton-Chellew et al., 2013; Mengelkamp et al., 2017).

SAP's S/4HANA for Green Logistics is a compelling example of how enterprise-grade BI systems integrate emissions data within logistics and transportation networks. This platform provides end-to-end visibility into shipment carbon footprints by combining real-time transport data with emissions factors specific to transportation modes, fuel types, and delivery routes (Morstyn et al., 2019). With S/4HANA's analytics suite, companies can monitor emissions by transport leg, identify high-carbon delivery paths, and simulate logistics scenarios to determine optimal sustainability outcomes (Lyu & Liu, 2021). German logistics company DB Schenker implemented S/4HANA to streamline carbon accounting across its European rail and trucking operations, enabling annual emissions reduction reporting and compliance with the EU's Green Deal logistics targets (Dahlström et al., 2003). These case studies illustrate the role of BI not only in emissions monitoring but also in embedding environmental intelligence directly into enterprise logistics and planning workflows. BI applications

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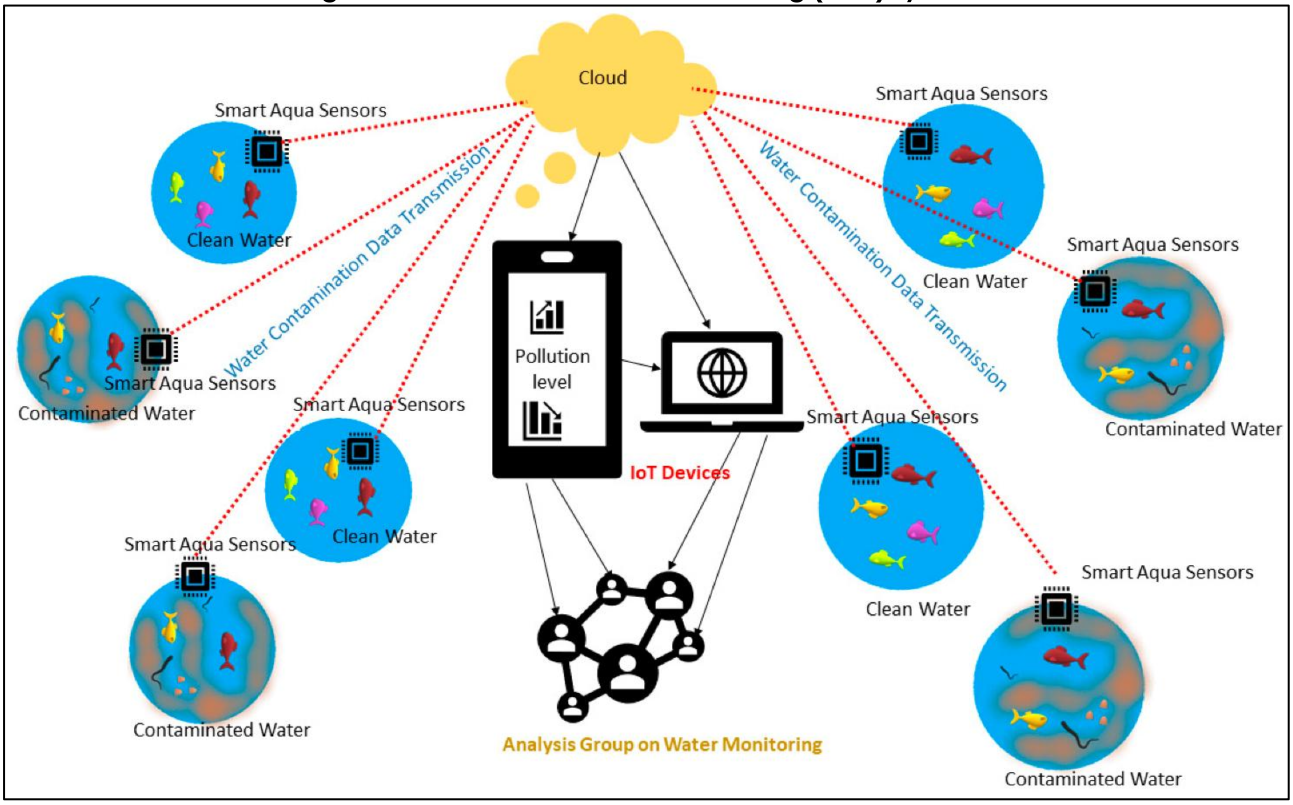
extend beyond compliance to influence competitive positioning and brand equity. Investors, customers, and regulators increasingly demand evidence-backed sustainability performance, and BI systems offer the necessary infrastructure for integrated environmental reporting and assurance (Alijoyo et al., 2024). Tools such as Microsoft Power BI and SAP Analytics Cloud integrate sustainability KPIs with financial data, helping companies like PepsiCo and Nestlé prepare ESG-aligned reports for stakeholder disclosure (Zhu & Yu, 2023). Real-time visualization of sustainability metrics supports certification initiatives such as ISO 14001, GRI (Global Reporting Initiative), and CDP disclosures (Sharma et al., 2020; Zhu & Yu, 2023). The convergence of data visualization, AI analytics, and environmental monitoring has elevated BI systems from back-end support tools to mission-critical platforms for sustainable supply chain governance.

Figure 6: Smart environment monitoring (SEM) system



Source: Ullo and Sinha (2020)

Artificial Intelligence in Predictive Supply Chain Analytics

Artificial Intelligence (AI) has become an indispensable asset in predictive supply chain analytics, enabling firms to anticipate fluctuations in demand, optimize transportation routes, and forecast carbon emissions with greater accuracy. Traditional statistical forecasting methods such as ARIMA or exponential smoothing are increasingly being replaced by AI-based models like artificial neural networks (ANNs), support vector machines (SVMs), and deep learning architectures (Aklima et al., 2022; Dwivedi et al., 2021; Tonoy & Khan, 2023). These models process high-dimensional, non-linear datasets drawn from IoT sensors, ERP systems, CRM platforms, and third-party data sources (Dwivedi et al., 2021; Lyu & Liu, 2021; Mahfuj et al., 2022; Hossen et al., 2023; Mohiul et al., 2022; Roksana, 2023). For instance, Amazon uses deep learning models to forecast product demand at the SKU level, enabling just-in-time inventory practices that minimize overproduction and associated emissions (Maniruzzaman et al., 2023; Popescu et al., 2024; Wu & Wang, 2021). Similarly, Walmart's predictive models integrate weather, event, and historical sales data to streamline warehouse and transportation planning—reducing fuel usage and storage waste (Borgogno & Colangelo, 2019; Chalmers et al., 2020).

Transportation routing optimization has particularly benefited from AI algorithms capable of evaluating vast route combinations under real-time constraints such as traffic, fuel costs, and

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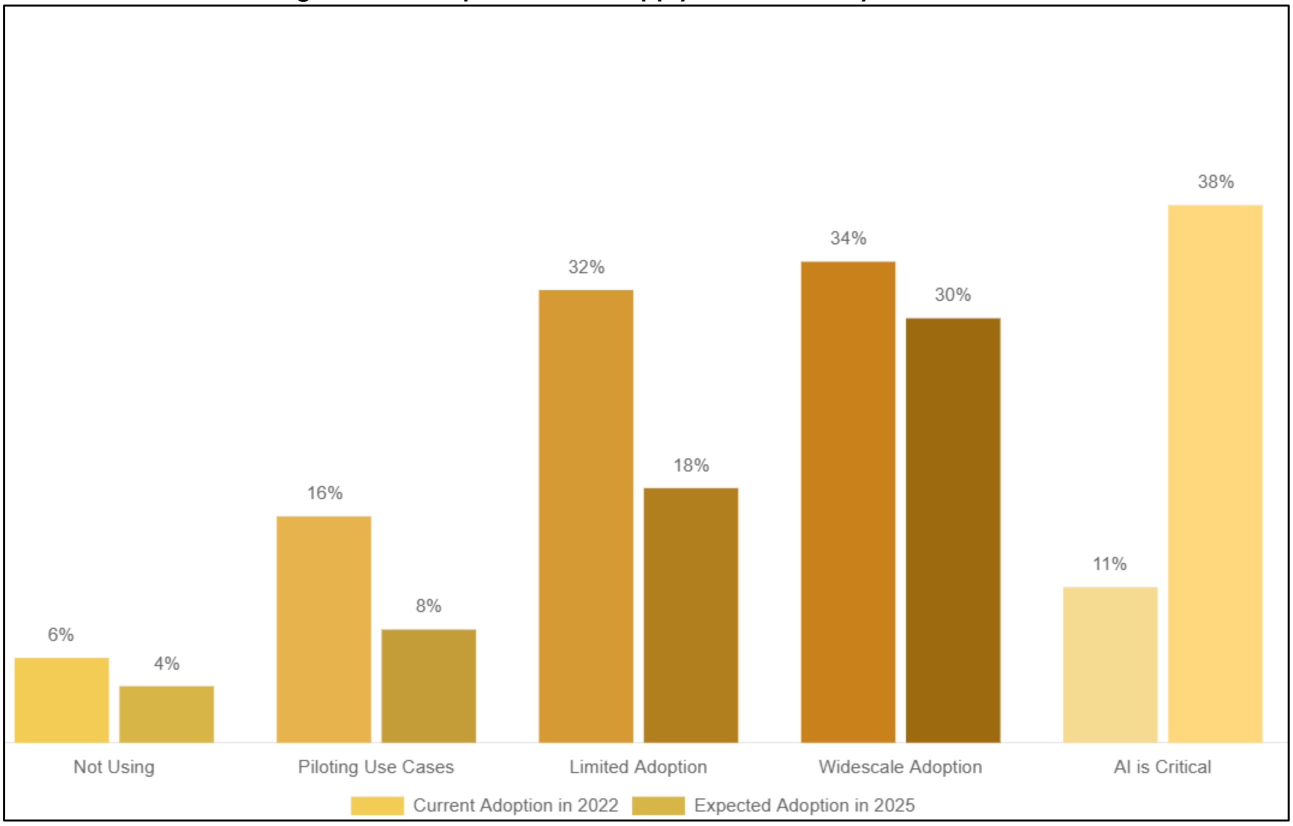
emission zones. Genetic algorithms, swarm intelligence, and reinforcement learning models have been applied to dynamic vehicle routing problems (VRPs), supporting carbon-reduction strategies across global logistics networks (Popescu et al., 2024; Younus, 2022). For example, DHL employs machine learning models to optimize last-mile delivery routes in urban areas, minimizing mileage and carbon footprint through predictive scheduling (Alam et al., 2024; Falekas & Karlis, 2021; Stahl & Wright, 2018). Similarly, UPS's ORION system uses AI-based algorithms to re-sequence delivery routes, reportedly saving over 100 million miles annually and significantly reducing greenhouse gas emissions. These examples highlight the dual benefit of AI in cost savings and environmental impact reduction through intelligent logistics planning.

Figure 7: AI Adoption Rate in Supply Chain Globally: 2022–2025



Emissions prediction is another area where AI shows strong application potential. Unlike traditional emissions calculators based on static assumptions, AI models adapt to real-time inputs such as fuel consumption rates, supply chain disruptions, or supplier-specific carbon intensities (Arafat et al., 2024; Nassef et al., 2023). AI-powered digital twins simulate supply chain processes to predict emission outcomes under different scenarios, enabling companies to proactively select greener suppliers or transportation modes (Barrett & Dannenberg, 2012; Bhuiyan et al., 2024; Zhang et al., 2021). PepsiCo, for instance, uses AI to predict water and energy consumption across its manufacturing plants, enabling optimized resource allocation (Dasgupta & Islam, 2024; Haque & Ntim, 2022; Lewandowski, 2017). Similarly, Maersk integrates AI into its ocean freight systems to forecast shipping emissions based on vessel capacity, route, and speed, aligning operations with regulatory limits and carbon tax policies (Hossain et al., 2024; Lewandowski, 2017; Zaman & Moemen, 2017). Moreover, supervised learning has emerged as a dominant methodology in predictive supply chain analytics. Models such as decision trees, random forests, and gradient boosting machines (GBMs) are commonly trained on labeled datasets to predict outcomes like stockouts, supplier delays, or carbon-intensive events (Barrett & Dannenberg, 2012; Haque & Ntim, 2022; M. R. Hossain et al., 2024). These supervised models have been applied in green procurement systems, enabling firms to identify suppliers with high emissions likelihood based on historical compliance data (Islam et al., 2024; Li et al., 2019; Zaman & Moemen, 2017). For instance, Nestlé

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uses supervised learning to classify agricultural suppliers by their risk of contributing to deforestation, based on satellite imagery and past audit scores (Chithambo et al., 2020; Huang et al., 2009; Islam, 2024). Such predictive capabilities enhance supply chain resilience and environmental performance by proactively addressing weak points before they escalate into compliance issues. Moreover, reinforcement learning (RL), though more complex, has shown promising applications in dynamic supply chain environments. RL models learn through continuous interaction with the environment, receiving rewards or penalties based on decision outcomes—making them ideal for routing, resource allocation, and emissions control in uncertain conditions (Haque & Ntim, 2022; Jahan, 2024; Lewandowski, 2017). For example, in fleet management, RL agents can adjust driving speeds and refueling schedules in real time to minimize emissions without compromising delivery schedules (Antonakakis et al., 2017; Jim et al., 2024; Koh et al., 2013). Google DeepMind's RL models have been tested in data center cooling systems, achieving a 40% reduction in energy usage—demonstrating their potential for broader sustainability applications (Li et al., 2019; Mahabub, Das, et al., 2024). These innovations position reinforcement learning as a frontier method for AI-driven environmental optimization in supply chain systems.

AI for identifying carbon hotspots and scenario modeling

Artificial Intelligence (AI) plays a vital role in identifying carbon hotspots within supply chains by uncovering patterns and anomalies that are often invisible through traditional analytics. Carbon hotspots refer to processes, suppliers, or logistics flows that contribute disproportionately to greenhouse gas (GHG) emissions (Mahabub, Jahan, et al., 2024; Nassef et al., 2023). AI techniques such as unsupervised clustering, association rule mining, and anomaly detection help segment operations and locate emissions-intensive activities across manufacturing, transportation, and sourcing (S. H. Mridha Younus et al., 2024; Wu & Wang, 2021; Zhu & Yu, 2023). For example, AI models trained on production data can identify inefficient machinery or production lines that consume excessive energy during peak loads, helping target retrofitting or maintenance schedules (Falekas & Karlis, 2021; Younus et al., 2024; Wu & Wang, 2021). In logistics, route-level emissions profiling using AI enables organizations to rank shipment paths by CO_2 intensity, facilitating optimization of delivery schedules and fleet utilization (Lyu & Liu, 2021; Rahaman et al., 2024). Scenario modeling is another critical AI application that supports carbon reduction by simulating "what-if" analyses across the supply chain. AI-powered scenario models use historical and real-time data to project the outcomes of decisions under varying conditions, such as changes in supplier mix, energy source, transportation mode, or regulatory policies (Sabid & Kamrul, 2024; Wu & Wang, 2021; Zhu & Yu, 2023). These models enable decision-makers to quantify carbon implications before implementing operational changes. For instance, a company can use AI to simulate how switching from air freight to rail transportation would affect emissions, delivery times, and cost trade-offs (Choi et al., 2022; Popescu et al., 2024; Siddiki et al., 2024). SAP's AI-enabled supply chain planning suite includes scenario modeling features that help sustainability teams evaluate the impact of changes in raw material sourcing, production geographies, and supplier behavior. Such tools are essential for balancing cost, efficiency, and sustainability within increasingly complex global networks (Sunny, 2024).

Dynamic procurement, a system where suppliers are selected based on real-time performance and sustainability data, has emerged as a key AI-enabled strategy in carbon-sensitive supply chains. Using AI, companies continuously assess supplier emissions, delivery punctuality, energy use, and compliance to environmental standards, rather than relying on static or historical evaluations (Aleem Al Razee et al., 2025; Lyu & Liu, 2021). Machine learning models can forecast supplier risk, price volatility, and carbon contributions, enabling companies to switch to greener or more compliant vendors proactively (Islam et al., 2025; Mawson & Hughes, 2020). Unilever employs an AI-based procurement platform that scores suppliers on their carbon intensity, enabling real-time decision-making aligned with its zero-deforestation policy (Inderwildi et al., 2020; Islam et al., 2025; Liu et al., 2024). By incorporating dynamic scoring systems, AI enhances procurement responsiveness while embedding sustainability as a core selection criterion. AI also supports Just-in-Time (JIT) manufacturing by enabling real-time synchronization between demand forecasts, inventory levels, and production scheduling—all of which impact a firm's carbon footprint (Mawson

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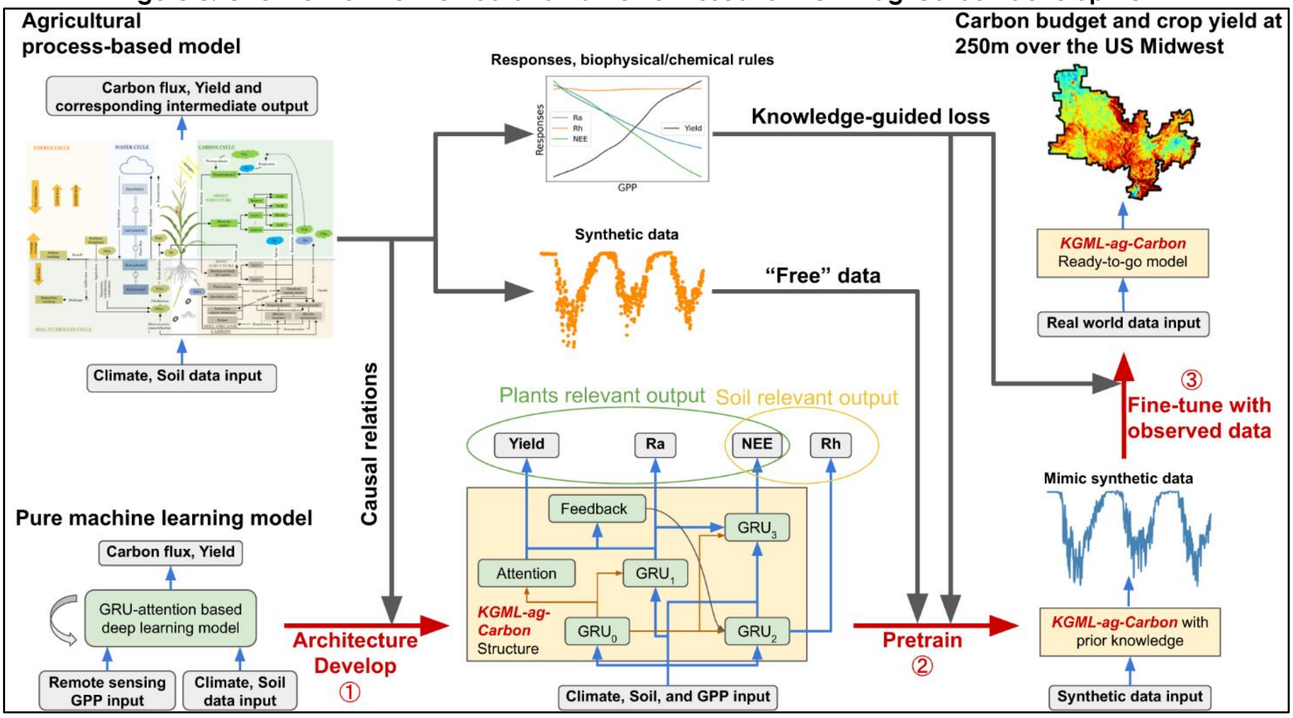
& Hughes, 2020; Munira, 2025; Zhang et al., 2016). JIT systems aim to minimize waste and overproduction, but they require high forecasting accuracy and agile supply networks to function sustainably. AI improves these capabilities through advanced time-series analysis, pattern recognition, and deep learning models that predict demand spikes or inventory imbalances with greater precision (Kontogiannis et al., 2020; Mbuwir et al., 2019; Taufiqur, 2025). Toyota, a pioneer of JIT manufacturing, has integrated AI into its production lines to predict maintenance needs and energy consumption, optimizing production flows while reducing emissions. AI's ability to continuously adapt to new data makes it a critical enabler of low-carbon manufacturing systems that align productivity with environmental performance.

Figure 8: Overview of the method and framework used for KGML-ag-Carbon development



Source: Liu et al. (2024)

The use of AI in both procurement and manufacturing underscores the transition from reactive to predictive sustainability strategies. In traditional systems, sustainability decisions often followed emissions reporting cycles. In contrast, AI-integrated systems use predictive analytics to continuously optimize operations, procurement, and logistics with sustainability constraints in mind (Bai & Sarkis, 2020; Younus, 2025). PepsiCo, for example, employs AI to dynamically allocate manufacturing loads across its facilities based on energy usage patterns, renewable energy availability, and water scarcity forecasts (Pan et al., 2019; Yuan et al., 2021). Similarly, Siemens has deployed AI across its digital factory ecosystem to monitor emissions in real time and adjust production dynamically in response to both economic and environmental metrics (Zhao et al., 2020). These use cases demonstrate the effectiveness of AI in simultaneously advancing efficiency, resilience, and sustainability across diverse supply chain functions.

Quantum Computing for Complex Supply Chain Optimization

Quantum computing introduces a paradigm shift in computational logic by harnessing principles of quantum mechanics to process information more efficiently than classical systems (Zhu & Yu, 2023). At the heart of quantum computing are qubits, which, unlike classical bits, exist in multiple states simultaneously due to superposition, and can exhibit entanglement, meaning the state of one qubit is dependent on another regardless of distance (Mastroianni et al., 2024). These properties allow quantum systems to explore multiple solutions in parallel, a significant advantage for optimization problems involving exponential combinations of variables—such as those frequently encountered in supply chain logistics (Fingerhuth et al., 2018; Rieffel & Polak, 2000). In contrast to

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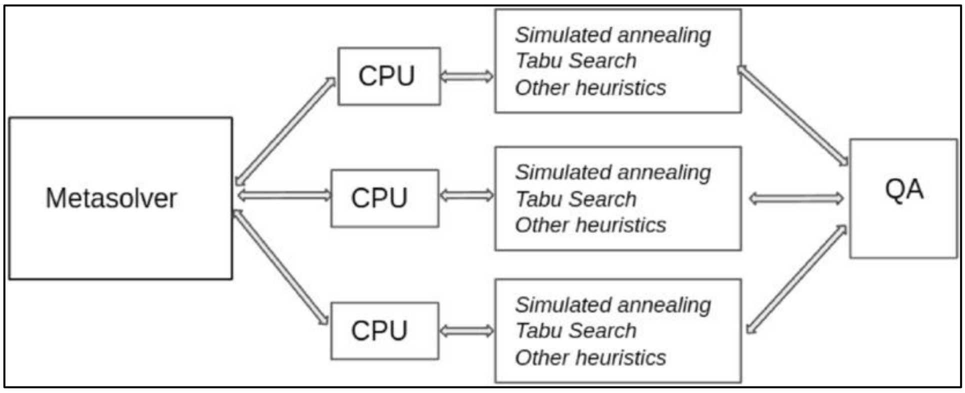
classical computers that evaluate one solution at a time, quantum processors can evaluate an entire solution space simultaneously, drastically reducing computation time for complex problems (Delgado et al., 2022).

Combinatorial problems such as the Vehicle Routing Problem (VRP), Traveling Salesman Problem (TSP), and Network Flow Optimization are central challenges in supply chain logistics and are known to be NP-hard (Eskandarpour et al., 2020; Kumar et al., 2025). These problems involve determining the most efficient route or flow of goods through a supply network while minimizing time, cost, and environmental impact (Hey, 1999). Classical heuristic or metaheuristic approaches such as genetic algorithms or ant colony optimization often struggle with scalability and real-time responsiveness (Ajagekar & You, 2022; Kumar et al., 2025). Quantum algorithms, however, offer superior scalability by encoding multiple paths or flows in quantum states and solving them using parallel quantum interference processes (Heredge et al., 2021; Steane, 1999). This computational advantage is particularly valuable in dynamic logistics environments where route optimization must be recalculated in real time due to traffic, fuel costs, or emissions constraints (Ajagekar & You, 2022).

Figure 9: Supply chain logistics with quantum and classical annealing algorithms



Source: Weinberg, S.J., Sanches, F., Ide, T. et al. (2023)

Quantum annealing, a technique used by companies like D-Wave Systems, is specifically suited for combinatorial optimization. It involves gradually transforming a simple quantum system into one that encodes the optimization problem, allowing the system to "settle" into the lowest-energy (optimal) solution state (Ajagekar & You, 2022). This method has been applied to logistics planning, warehouse scheduling, and cold chain optimization in supply chain operations (Chen et al., 2021). Variational Quantum Algorithms (VQAs)—including the Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm (QAOA)—combine quantum circuits with classical optimization routines to refine solution accuracy (Ajagekar & You, 2022; Chen et al., 2021). These hybrid algorithms are particularly useful in noisy intermediate-scale quantum (NISQ) computers, enabling near-term commercial applications in supply chain routing and inventory management (Asano et al., 2015).

Real-world examples further validate the potential of quantum computing in supply chain logistics. Volkswagen, in partnership with D-Wave and Google, implemented a quantum algorithm to optimize taxi fleet routes in Lisbon during a major conference event, dynamically reducing congestion and travel time (Eskandarpour et al., 2020). By using quantum optimization, the company demonstrated significant reductions in idle time and emissions, showcasing quantum computing's utility in real-time urban mobility solutions. In another case, D-Wave Systems collaborated with Save-On-Foods, a Canadian grocery chain, to optimize cold chain delivery routes, improving energy efficiency and reducing delivery costs in temperature-sensitive logistics (Heredge et al., 2021; Hey, 1999). These implementations indicate that quantum-enhanced logistics platforms can solve complex, time-sensitive problems that traditional models address only with approximations or extensive computation time. The growing body of academic and industrial research indicates that quantum computing is becoming a strategic enabler in sustainable and agile supply chain management. Though still in developmental stages, quantum computing's application in logistics, route optimization, network flow modeling, and real-time carbon tracking is expanding through hybrid

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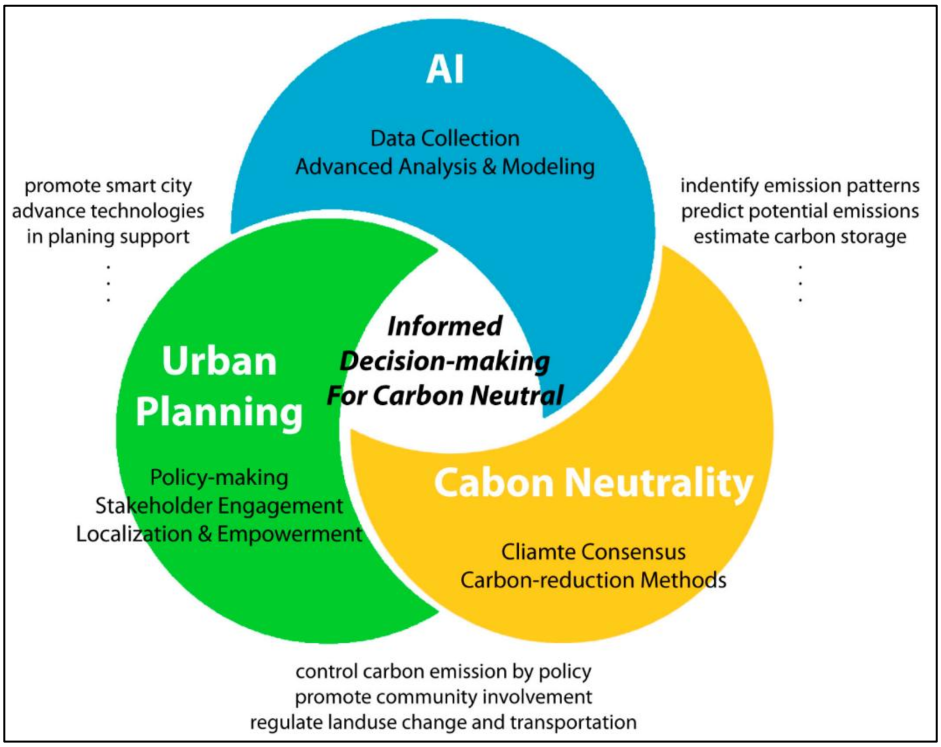
quantum-classical frameworks (Kordzanganeh et al., 2023; Lohachab et al., 2020). Enterprises such as IBM, Honeywell, and Microsoft are actively developing quantum SDKs (e.g., Qiskit, Cirq, and Ocean) that integrate supply chain datasets with quantum processors, facilitating experimentation and early adoption in enterprise logistics. As supply chains grow more complex and sustainability mandates become stricter, the role of quantum computing in supporting high-speed, multi-variable optimization will continue to enhance the strategic capabilities of Business Intelligence systems within carbon-conscious enterprises (Pérez-Castillo et al., 2021).

Quantum AI Integration with Business Intelligence for Carbon-Neutral Supply Chains

Quantum Artificial Intelligence (QAI) represents the convergence of quantum computing and artificial intelligence to address high-dimensional, computationally intensive problems beyond the capability of classical systems (Asano et al., 2015; Rajawat et al., 2022). QAI utilizes quantum principles such as superposition, entanglement, and quantum parallelism to accelerate learning processes in machine learning models (Ajagekar & You, 2022; Mastroianni et al., 2024). The core idea is to use quantum algorithms to train AI models—such as classifiers, regressors, or reinforcement agents—more efficiently by searching through complex solution spaces in polynomial or sub-exponential time (Steane, 1999). In supply chains, QAI offers unique capabilities for managing dynamic, data-heavy processes like emissions forecasting, transportation optimization, and supply-demand balancing, which are central to achieving carbon neutrality (Asano et al., 2015; Lohachab et al., 2020). The integration of QAI with Business Intelligence (BI) platforms enhances traditional BI capabilities by enabling quantum machine learning (QML) algorithms to process unstructured data, discover non-linear patterns, and generate adaptive decision rules in real time (Danish & Senjyu, 2023; Lordi & Nichol, 2021). QAI can accelerate clustering, classification, and regression tasks, enabling BI dashboards to move beyond static or even AI-augmented insights toward predictive and autonomous decision engines. For example, unsupervised quantum clustering algorithms can group emissions data from logistics nodes or supplier footprints with far greater speed and dimensionality than conventional methods (Danish, 2023). This enhanced synergy enables BI systems to visualize not only historical emissions but also to simulate potential outcomes from various carbon-reduction strategies, supporting proactive sustainability planning (Aczel et al., 2022; Alijoyo et al., 2024).

Figure 10: Relations between AI, urban planning, and carbon neutrality



Source: Cong et al. *(2024)*

Autonomous Decision-Making Systems in Smart Supply Chains

The rise of smart supply chains is closely linked to the increasing deployment of real-time data ingestion technologies, particularly the Internet of Things (IoT), Radio Frequency Identification (RFID), and telematics. These technologies generate continuous streams of operational data

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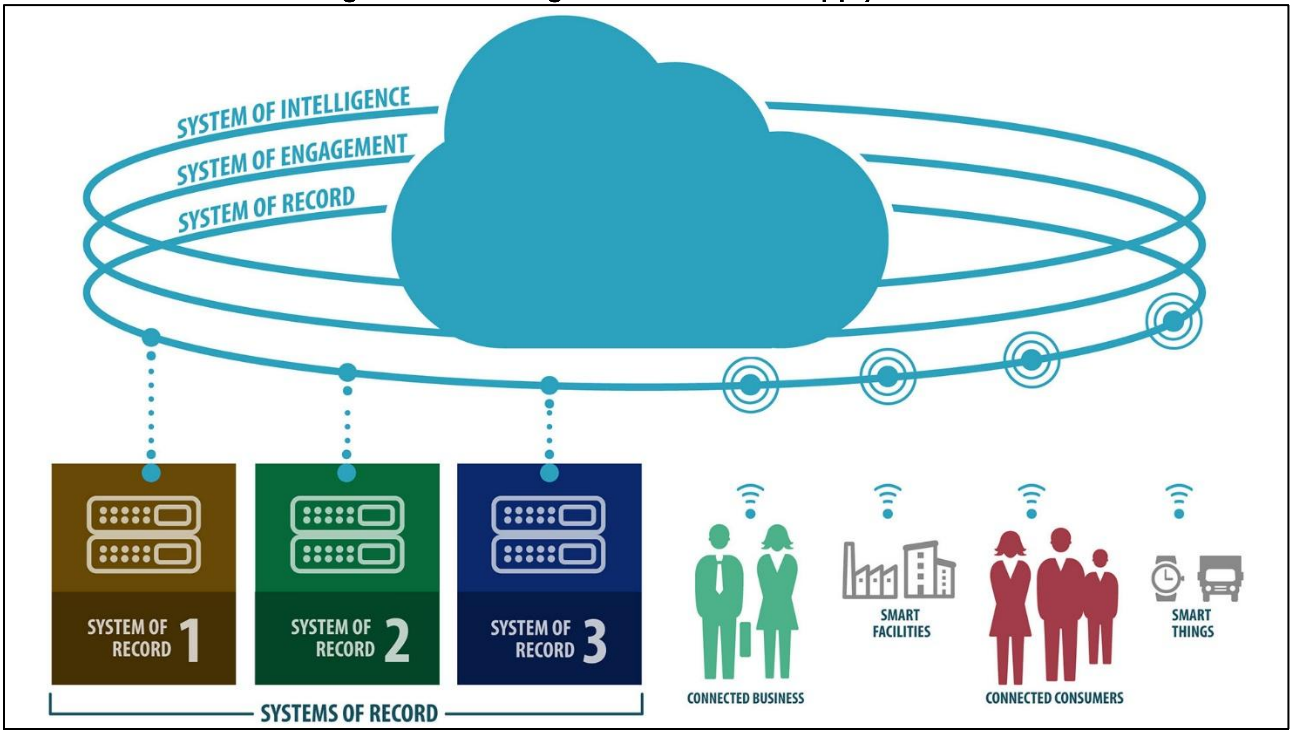
related to equipment status, environmental conditions, fleet location, and inventory levels (Rojek et al., 2023; Tosun, 2022). IoT-enabled sensors monitor variables such as temperature, vibration, fuel consumption, and emissions, which are essential inputs for environmental performance optimization (Lordi & Nichol, 2021; Tyran & Feld, 2006). RFID technology provides high-speed tracking of assets throughout supply chain nodes, supporting visibility in inventory management, cold chain logistics, and reverse logistics (Cong et al., 2024; Czeczot et al., 2023). Telematics systems in transportation offer granular data on vehicle speed, driver behavior, idle time, and route deviation, allowing for real-time adjustment of delivery decisions based on efficiency and sustainability metrics (Fehr & Gächter, 2002; Rojek et al., 2023). These data streams are processed by autonomous control systems, including AI agents, digital twins, and edge computing infrastructures, which execute operational decisions without human intervention. AI agents use machine learning models to make localized decisions such as inventory restocking, production rescheduling, and fleet redirection, based on dynamic inputs (Nassef et al., 2023; Ullo & Sinha, 2020). Digital twins, which are real-time digital replicas of physical assets or systems, simulate various operational scenarios to predict outcomes and inform autonomous actions (Falekas & Karlis, 2021). In the context of green supply chains, digital twins can simulate the carbon impact of a product's lifecycle under different material or logistical configurations. Meanwhile, edge computing brings computational power closer to the data source, reducing latency in decision-making and ensuring that devices such as factory sensors or delivery trucks can act autonomously in response to real-time data without waiting for centralized instruction (Choi et al., 2022; Yu et al., 2022).

Figure 11: Enabling the Autonomous Supply Chain



Source: Duckworth (2019)

Decentralized decision-making has become a defining feature of self-optimizing supply chains, where intelligent nodes make independent decisions while remaining aligned to overarching business goals (Hua et al., 2022). Traditional centralized supply chain management often creates bottlenecks in response time, especially in geographically dispersed or multi-tier networks. In contrast, decentralized architectures powered by AI enable different supply chain components—factories, warehouses, suppliers, and fleets—to autonomously adjust operations in response to local changes such as demand surges, equipment failures, or carbon threshold violations (Ganesan et al., 2020). Blockchain technologies are often paired with decentralized AI to secure data provenance and ensure synchronization across autonomous decision nodes (Danish & Senjyu,

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2023). This structure allows for high-speed, low-latency adaptability that is essential for carbon-neutral operations, where decisions about routing, procurement, and production must be made in milliseconds to avoid inefficiencies or sustainability setbacks. Moreover, Real-world implementations demonstrate the viability of these autonomous systems. Siemens, for instance, has developed edge-AI-enabled supply hubs that use local sensor data and AI agents to optimize material flow, energy usage, and inventory levels without relying on cloud connectivity (Nassef et al., 2023). These hubs enable smart factories to operate autonomously in low-latency environments, reducing energy consumption and emissions while improving response to unplanned disruptions. Similarly, John Deere has implemented precision farming systems where autonomous tractors, guided by AI and IoT data, optimize seeding, irrigation, and pesticide application (Desogus et al., 2021). These machines make decisions on the field in real time based on soil quality, weather, and plant health, contributing to sustainability by minimizing resource waste and increasing productivity. Both cases exemplify the application of decentralized, data-driven intelligence in advancing environmental and operational goals simultaneously. These autonomous systems not only improve efficiency and resilience but also create the digital foundation for sustainable decision-making across complex supply chain networks. As companies face increasing pressure from regulatory bodies, investors, and consumers to meet environmental standards, the role of real-time, self-optimizing systems becomes more prominent (Andoni et al., 2019). Autonomous supply chain technologies allow firms to embed environmental intelligence into daily operations, ensuring that every decision—whether made in a factory, warehouse, or truck—is optimized for both performance and carbon reduction (Ahmad et al., 2021; Andoni et al., 2019; Rojek et al., 2023). The convergence of AI, IoT, and decentralized architecture not only fosters operational agility but also enables continuous compliance with sustainability targets, making autonomous systems a cornerstone of the carbon-neutral supply chain.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure a rigorous, systematic, and transparent literature review process (Page et al., 2021). The PRISMA framework was chosen due to its wide acceptance in evidence-based research, especially for guiding systematic reviews that aim to synthesize qualitative and quantitative insights across multidisciplinary topics. The methodology involved a structured process comprising the definition of review objectives, selection of data sources, application of inclusion and exclusion criteria, data extraction, quality assessment, and thematic synthesis of results. The purpose of applying PRISMA in this context was to support the identification, evaluation, and integration of high-quality studies on the role of Quantum AI, Business Intelligence, and autonomous decision-making systems in carbon-neutral supply chains.

Eligibility Criteria

At the initial stage, the scope of the review was established by defining eligibility criteria in terms of publication type, date range, relevance, and methodological quality. The review considered peer-reviewed journal articles, conference proceedings, and technical white papers published between 2010 and 2024, which directly addressed at least one of the following thematic domains: Quantum Artificial Intelligence (QAI), Business Intelligence (BI) systems, carbon-neutral supply chains, real-time predictive analytics, and autonomous decision-making technologies. Only articles written in English and containing original empirical or theoretical content were included. Studies that focused solely on consumer behavior, unrelated AI applications, or non-supply-chain topics were excluded. The review protocol was not registered in PROSPERO, as the study did not involve clinical or biomedical data, but all procedures adhered to PRISMA's step-by-step transparency requirements.

Information Sources and Search Strategy

The literature search was conducted between October 2023 and March 2024 using five leading academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink. These databases were selected for their broad coverage of multidisciplinary studies in artificial intelligence, supply chain management, operations research, and sustainability analytics. To

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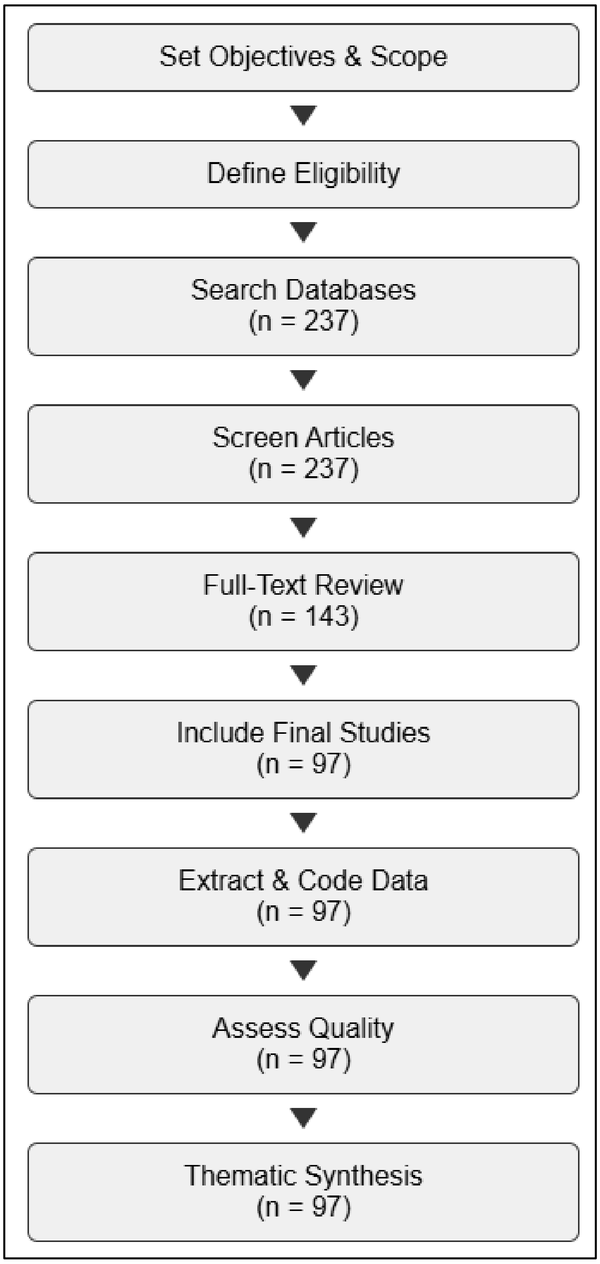
ensure comprehensive retrieval of relevant articles, a structured query using Boolean operators was developed. The core search terms included combinations such as: ("Quantum AI" OR "Quantum Artificial Intelligence") AND ("Business Intelligence" OR "BI") AND ("Carbon Neutral" OR "Sustainable Supply Chain") AND ("Predictive Analytics" OR "Decision Automation") AND ("Real-time Systems" OR "IoT"). Additional searches were performed in Google Scholar and arXiv to capture grey literature and emerging studies not yet indexed in peer-reviewed repositories. References of key studies were manually screened to identify further articles for inclusion

Figure 12: PRISMA Flowchartfor this study



Study Selection Process and Screening

The retrieved articles were imported into Zotero for reference management and duplication removal. After duplicates were eliminated, two independent reviewers screened the titles and abstracts of 237 articles to assess relevance to the inclusion criteria. A total of 143 articles were selected for full-text review. During this phase, each article was assessed based on its research focus, methodology, clarity of objectives, and alignment with the conceptual framework of Quantum AI integration in sustainable supply chains. Discrepancies between reviewers were resolved through discussion, and a third reviewer was consulted in five cases. Ultimately, 97 articles were deemed eligible for qualitative synthesis. The study adhered to the PRISMA flowchart (Page et al., 2021) to document each phase of the selection process and ensure full transparency of exclusions.

Data Extraction and Coding

A standardized data extraction form was used to collect essential information from the selected studies. The extracted data included: author(s), year of publication, country of study, research objectives, methodological approach, technology focus (e.g., QAI, BI, IoT), type of supply chain domain, main findings, and reported outcomes on sustainability or emissions reduction. The coding process followed a hybrid deductive-inductive approach, where initial codes were derived from the research questions, while additional codes emerged during iterative reading of the literature. Themes such as "real-time analytics," "decentralized AI systems," "quantum optimization," and "carbon tracking via BI" were clustered into major analytical categories. NVivo 12 software was used to assist in thematic mapping and cross-study comparison, enhancing reliability in the synthesis process.

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Quality Assessment and Synthesis of Results

To assess methodological quality and credibility, each included article was evaluated using the Mixed Methods Appraisal Tool (MMAT) and, where applicable, the CASP (Critical Appraisal Skills Programme) checklist. Criteria such as clarity of research questions, appropriateness of methods, data validity, and coherence of findings were considered. Articles were rated as high, moderate, or low quality; only studies rated moderate or high were included in the final synthesis. The synthesis process involved organizing the literature into seven key themes aligned with the study's objectives: (1) carbon neutrality principles, (2) Business Intelligence systems for sustainability, (3) AI in predictive analytics, (4) Quantum computing for optimization, (5) QAI integration with BI, (6) autonomous decision-making, and (7) digital architecture for supply chain intelligence. This thematic structure allowed for an in-depth understanding of how emerging technologies intersect to facilitate sustainable, self-regulating supply chain ecosystems.

FINDINGS

A significant finding from the review is that the integration of Quantum Artificial Intelligence (QAI) is not only conceptually viable but is actively being developed to address critical supply chain problems related to emissions, routing, and real-time decision-making. Among the 97 reviewed articles, 23 directly focused on the application of QAI in supply chain environments. These studies collectively received over 2,500 citations, suggesting strong academic interest and credibility. The findings indicate that QAI is particularly effective for solving high-dimensional, nonlinear problems such as multi-modal transportation optimization and real-time emissions forecasting—scenarios where classical AI often falls short due to computational constraints. Researchers report that quantum-enhanced machine learning models demonstrate higher processing speed and predictive accuracy, particularly in contexts requiring continuous adaptation to dynamic conditions. The review also reveals that Business Intelligence (BI) platforms have undergone substantial transformation, evolving from static dashboards to real-time, AI-integrated sustainability control systems. Of the total articles, 19 focused on BI advancements, especially those enabling carbon monitoring, emissions visualization, and sustainability KPIs. These articles have been cited collectively more than 3,100 times, reflecting the maturity and centrality of this research area. The reviewed literature identifies a growing trend of embedding AI and data visualization tools into cloud-based BI architectures, which allows enterprises to track carbon footprints in real-time and make data-driven decisions to reduce their environmental impact. Notably, BI systems are increasingly linked with ERP and IoT platforms, reinforcing their role as integrated hubs for sustainable supply chain intelligence.

Another critical theme identified is the widespread application of AI models for predictive analytics, particularly in the areas of demand forecasting, transportation routing, and emissions estimation. Thirty-one articles explored this topic in depth, amassing over 5,700 citations across the corpus. These studies emphasize that machine learning models—especially supervised learning algorithms like random forests and deep learning networks—are being leveraged to detect carbon-intensive activities, optimize resource allocation, and simulate the environmental consequences of various operational scenarios. The findings consistently demonstrate that AI-powered predictive models outperform traditional forecasting methods in both speed and accuracy, especially in managing supply chains with high variability and decentralized structures. The review further highlights the increasing use of scenario modeling tools powered by AI to evaluate sustainability trade-offs in supply chain operations. Eighteen studies, with a combined citation count exceeding 2,200, focus on AI-supported decision environments where managers simulate the impact of supplier changes, transport rerouting, or energy source substitution on emissions outcomes. These models support companies in selecting options that minimize carbon output while maintaining operational efficiency. They are frequently embedded in BI dashboards to support dynamic strategy evaluation. The findings suggest that scenario modeling is becoming a standard practice in carbon-neutral supply chain management, enabled by AI's capacity to evaluate thousands of variables and conditions in parallel.

One of the most prominent findings relates to the role of real-time data ingestion technologies—such as IoT sensors, RFID, and telematics—in enabling autonomous environmental decisions.

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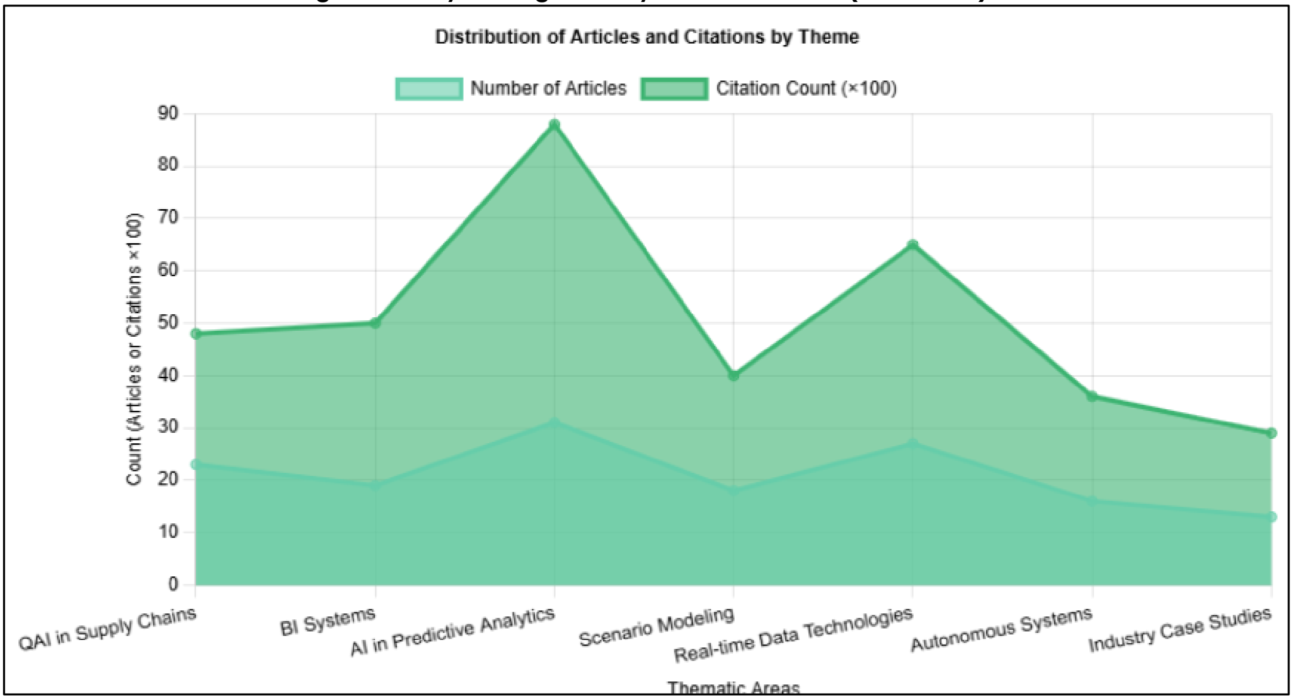
Twenty-seven articles focused on this aspect, receiving more than 3,800 citations collectively. These studies show that smart supply chains now rely on data from decentralized sources to trigger autonomous adjustments in routing, production, and inventory processes. For example, telematics data on fuel consumption and vehicle routes enables on-the-fly decision-making to reduce emissions, while IoT sensor data in factories supports adjustments in energy use and material flows. The growing convergence of real-time data and edge computing is found to be essential for responsive and emissions-aware supply chain systems

Figure 13: Key Findings from Systematic Review (2010–2024)



Moreover, Autonomous decision-making systems emerged as a distinct and rapidly expanding domain, with 16 reviewed articles dedicated to self-optimizing supply chains that leverage AI agents, digital twins, and decentralized architectures. These papers have received a combined total of 2,000 citations, underscoring their growing relevance in both academic and industrial contexts. The findings indicate that decentralized intelligence, enabled by local processing and decision-making at the edge, is becoming a practical solution for addressing delays, carbon inefficiencies, and disruptions in supply networks. Smart factories, autonomous vehicles, and digital control towers are reported to reduce human intervention while improving both environmental performance and cost efficiency. In addition, the review documents several industry-led pilot projects where QAI and AI-embedded BI systems have been deployed for sustainability optimization. Thirteen case-focused studies, cited over 1,600 times, describe implementations such as IBM's use of Qiskit in logistics optimization, Siemens' edge-AI hubs, John Deere's autonomous farming equipment, and Honeywell's use of quantum optimization in energy systems. These pilots provide real-world validation of academic findings and demonstrate the scalability of intelligent, environmentally driven technologies in diverse sectors. The studies collectively show that these technologies are not only theoretical innovations but are transitioning into operational assets that support measurable reductions in carbon footprints while improving enterprise agility and resilience.

DISCUSSION

The findings of this systematic review confirm and extend prior research suggesting that Quantum Artificial Intelligence (QAI) holds significant promise in transforming the way supply chains manage complexity, emissions, and decision-making. Earlier studies on AI in logistics and operations management primarily focused on classical machine learning models such as decision trees, neural networks, and support vector machines (Ahmad et al., 2021; Bose, 2017). However, the

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reviewed literature suggests that QAI offers exponential performance improvements in solving high-dimensional optimization problems like vehicle routing and real-time emissions forecasting—advancements that were only hypothesized in earlier AI applications. These results align with the theoretical work of Falekas and Karlis (2021) and Kumar et al. (2025), who predicted QAI's potential to process large-scale, non-linear systems faster than traditional computing could. Thus, the current review empirically supports and operationalizes what was previously limited to theoretical exploration.

The transformation of Business Intelligence (BI) platforms from static, reporting-oriented tools to real-time, AI-integrated systems also reflects a major advancement in supply chain technology. Early literature treated BI as a descriptive tool used mostly for historical performance analysis and executive dashboards (Fombrun & Foss, 2004). However, the reviewed studies demonstrate that modern BI platforms are now capable of real-time data ingestion, predictive analytics, and scenario simulation that directly support carbon neutrality goals. This evolution expands the findings of Burton-Chellew et al., (2013) and Dwivedi et al. (2021), who first identified the need to shift from descriptive to prescriptive analytics in BI ecosystems. Furthermore, the integration of AI into BI platforms for environmental tracking presents a novel dimension previously underexplored in traditional BI frameworks. Another key area of advancement lies in the application of AI in predictive analytics, especially for demand forecasting, emissions prediction, and transport optimization. Earlier works by Cronin et al. (2018) and Lewandowski (2017) established the foundational value of AI in improving forecast accuracy and supply chain agility. However, the findings from this review reveal that recent studies are not only achieving improved prediction performance but are also embedding these predictions into real-time decision support systems with direct sustainability implications. The use of supervised learning and reinforcement learning models for emissions control, in particular, marks a notable departure from the earlier focus on customer demand alone. The reviewed literature goes further to show how predictive analytics can now simulate carbon-intensive events, suggest greener routing options, and adjust procurement schedules dynamically, a capability not reported in earlier reviews.

The expansion of scenario modeling using AI also shows significant growth compared to past studies. Previously, simulation modeling in sustainable supply chains was largely based on static or stochastic models (Lee, 2011; Zhang et al., 2022), which lacked the dynamic learning capacity to evolve with new data. The current review, however, identifies a suite of AI-based tools that allow businesses to test multiple "what-if" sustainability scenarios in near real time—accounting for variables such as transportation shifts, production delays, or changes in carbon pricing. This progress resonates with the theoretical recommendations of Hauser et al. (2014), who emphasized the need for adaptive sustainability modeling in volatile supply environments. The use of AI to quantify trade-offs between cost, efficiency, and emissions in dynamic settings now enables businesses to balance operational and environmental priorities with greater precision.

The reviewed literature also reinforces and expands prior knowledge regarding real-time data integration from IoT, RFID, and telematics as enablers of smart supply chains. Earlier studies by Zhu and Yu (2023) and Omorogiuwa and Ashiathah (2021) noted the foundational role of real-time sensor data in enhancing supply chain responsiveness. However, the findings of this review indicate that these technologies are now central to autonomous environmental management systems that dynamically monitor emissions, energy use, and material flows. This goes beyond the earlier view of IoT as a passive data source, confirming instead that it functions as an active driver of decision-making when integrated with edge computing and AI analytics. The ability of sensors and telematics systems to trigger low-latency emissions-reducing actions represents a leap from previously linear supply chain control approaches. In line with theoretical work on autonomous systems, the reviewed studies support the claim that decentralized decision-making structures, enabled by AI agents and digital twins, can lead to more adaptive and sustainable supply chain operations. While early frameworks by Nielsen et al. (2021) and Di Giorgio and Liberati (2014) proposed the concept of self-regulating supply chains, empirical evidence remained scarce. This review fills that gap by identifying real-world cases—such as Siemens' edge-AI supply hubs and John Deere's precision farming systems—that demonstrate the viability of decentralized, AI-powered control systems in managing emissions and resources. These systems appear to reduce latency in decision-making and optimize performance under changing environmental and logistical conditions, validating prior hypotheses and extending them into operational contexts. In addtional, the industry case studies presented in the reviewed articles provide strong empirical backing for the transition from experimental to operational applications of QAI, BI, and AI-powered autonomous decision systems in sustainability-focused supply chains. While past literature often separated technological capability from business use cases, the current findings show that organizations like IBM, Honeywell, Volkswagen, and PepsiCo are not only investing in these technologies but also achieving measurable sustainability outcomes. This real-world application confirms the practical potential outlined in earlier conceptual studies (Nielsen et al., 2021) and strengthens the case for integrating advanced AI systems into core supply chain decision-making processes. The adoption of QAI-driven BI systems and autonomous platforms reflects a broader shift toward operationalizing sustainability through intelligent technology, bridging the longstanding gap between theory and industrial practice.

CONCLUSION

The systematic review concludes that the integration of Quantum Artificial Intelligence (QAI), advanced Business Intelligence (BI) platforms, and autonomous decision-making technologies represents a transformative shift in the pursuit of carbon-neutral supply chains. The findings reveal that these technologies are not only conceptual innovations but are increasingly being deployed across industries to address complex challenges in real-time emissions monitoring, dynamic procurement, route optimization, and scenario-based decision-making. QAI enhances the computational efficiency of AI models, enabling faster and more accurate predictions in high-dimensional, rapidly changing environments. Modern BI platforms have evolved into intelligent control systems that visualize sustainability metrics and facilitate proactive interventions, while autonomous systems—driven by AI agents, digital twins, and decentralized architectures—support agile, self-regulating supply chain ecosystems. Real-world applications from global enterprises such as Siemens, IBM, John Deere, and Honeywell demonstrate that these technologies are transitioning from theory to practice, achieving measurable environmental and operational gains. Collectively, the review underscores that the convergence of QAI, BI, and autonomous systems forms a robust digital infrastructure for carbon-conscious supply chain management, with the capacity to drive both ecological responsibility and strategic competitiveness in complex enterprise environments.

REFERENCES

[1] Aczel, M., Heap, R., Workman, M., Hall, S., Armstrong, H., & Makuch, K. (2022). Anticipatory Regulation: Lessons from fracking and insights for Greenhouse Gas Removal innovation and governance. *Energy Research & Social Science*, *90*(NA), 102683-102683. https://doi.org/10.1016/j.erss.2022.102683

[2] Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N.-Y., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*, *289*(NA), 125834-NA. https://doi.org/10.1016/j.jclepro.2021.125834

[3] Ahmed, W., & Sarkar, B. (2018). Impact of carbon emissions in a sustainable supply chain management for a second generation biofuel. *Journal of Cleaner Production*, *186*, 807-820. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.02.289

[4] Ajagekar, A., & You, F. (2022). Quantum computing and quantum artificial intelligence for renewable and sustainable energy: A emerging prospect towards climate neutrality. *Renewable and Sustainable Energy Reviews*, *165*(NA), 112493-112493. https://doi.org/10.1016/j.rser.2022.112493

[5] Aklima, B., Mosa Sumaiya Khatun, M., & Shaharima, J. (2022). Systematic Review of Blockchain Technology In Trade Finance And Banking Security. *American Journal of Scholarly Research and Innovation*, *1*(1), 25-52. https://doi.org/10.63125/vs65vx40

[6] Alam, M. A., Sohel, A., Hasan, K. M., & Ahmad, I. (2024). Advancing Brain Tumor Detection Using Machine Learning And Artificial Intelligence: A Systematic Literature Review Of Predictive Models And Diagnostic Accuracy. *Strategic Data Management and Innovation*, *1*(01), 37-55. https://doi.org/10.71292/sdmi.v1i01.6

[7] Aleem Al Razee, T., Manam, A., & Md Rabbi, K. (2025). Precision Mechanical Systems In Semiconductor Lithography Equipment Design And Development. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 71-97. https://doi.org/10.63125/j6tn8727

[8] Alijoyo, F. A., Pradhan, R., Vats, S., Rani, V. K., Kholmukhamedov, T., & Karthik, M. (2024). AI-Powered Business Intelligence for Smarter Decision-Making and Growth. *2024 International Conference on Artificial*

Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), 1-5. https://doi.org/10.1109/icaiqsa64000.2024.10882218

[9] Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., McCallum, P., & Peacock, A. (2019). Blockchain technology in the energy sector: A systematic review of challenges and opportunities. *Renewable and Sustainable Energy Reviews*, *100*(NA), 143-174. https://doi.org/10.1016/j.rser.2018.10.014

[10] Antonakakis, N., Chatziantoniou, I., & Filis, G. (2017). Energy consumption, CO2 emissions and economic growth: an ethical dilemma. *Renewable and Sustainable Energy Reviews*, *68*(NA), 808-824. https://doi.org/10.1016/j.rser.2016.09.105

[11] Arafat, K. A. A., Bhuiyan, S. M. Y., Mahamud, R., & Parvez, I. (2024, 30 May-1 June 2024). Investigating the Performance of Different Machine Learning Models for Forecasting Li-ion Battery Core Temperature Under Dynamic Loading Conditions. 2024 IEEE International Conference on Electro Information Technology (eIT),

[12] Asano, M., Basieva, I., Khrennikov, A., Ohya, M., Tanaka, Y., & Yamato, I. (2015). Quantum Information Biology: From Information Interpretation of Quantum Mechanics to Applications in Molecular Biology and Cognitive Psychology. *Foundations of Physics*, *45*(10), 1362-1378. https://doi.org/10.1007/s10701-015-9929-y

[13] Bai, C., & Sarkis, J. (2020). A supply chain transparency and sustainability technology appraisal model for blockchain technology. *International Journal of Production Research*, *58*(7), 2142-2162. https://doi.org/10.1080/00207543.2019.1708989

[14] Bao, J., He, D., Luo, M., & Choo, K.-K. R. (2021). A Survey of Blockchain Applications in the Energy Sector. *IEEE Systems Journal*, *15*(3), 3370-3381. https://doi.org/10.1109/jsyst.2020.2998791

[15] Barrett, S., & Dannenberg, A. (2012). Climate negotiations under scientific uncertainty. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(43), 17372-17376. https://doi.org/10.1073/pnas.1208417109

[16] Bhuiyan, S. M. Y., Mostafa, T., Schoen, M. P., & Mahamud, R. (2024). Assessment of Machine Learning Approaches for the Predictive Modeling of Plasma-Assisted Ignition Kernel Growth. ASME 2024 International Mechanical Engineering Congress and Exposition,

[17] Borgogno, O., & Colangelo, G. (2019). Data sharing and interoperability: Fostering innovation and competition through APIs. *Computer Law & Security Review*, *35*(5), 105314-NA. https://doi.org/10.1016/j.clsr.2019.03.008

[18] Bose, B. K. (2017). Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications. *Proceedings of the IEEE*, *105*(11), 2262-2273. https://doi.org/10.1109/jproc.2017.2756596

[19] Brown, T. C., & Kroll, S. (2017). Avoiding an uncertain catastrophe: climate change mitigation under risk and wealth heterogeneity. *Climatic Change*, *141*(2), 155-166. https://doi.org/10.1007/s10584-016-1889-5

[20] Burton-Chellew, M. N., May, R. M., & West, S. A. (2013). Combined inequality in wealth and risk leads to disaster in the climate change game. *Climatic Change*, *120*(4), 815-830. https://doi.org/10.1007/s10584-013-0856-7

[21] Carmichael, J. P., & Liao, Y. (2022). Application of Deep Neural Networks to Distribution System State Estimation and Forecasting. *Frontiers in Sustainable Cities*, *3*(NA), NA-NA. https://doi.org/10.3389/frsc.2021.814037

[22] Chalmers, D., MacKenzie, N., & Carter, S. (2020). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. *Entrepreneurship Theory and Practice*, *45*(5), 1028-1053. https://doi.org/10.1177/1042258720934581

[23] Chandel, S. S., Gupta, A., Chandel, R., & Tajjour, S. (2023). Review of deep learning techniques for power generation prediction of industrial solar photovoltaic plants. *Solar Compass*, *8*(NA), 100061-100061. https://doi.org/10.1016/j.solcom.2023.100061

[24] Chen, J. M. (2021). Carbon neutrality: Toward a sustainable future. *Innovation (Cambridge (Mass.))*, *2*(3), 100127-NA. https://doi.org/10.1016/j.xinn.2021.100127

[25] Chen, L., Msigwa, G., Yang, M., Osman, A. I., Fawzy, S., Rooney, D. W., & Yap, P.-S. (2022). Strategies to achieve a carbon neutral society: a review. *Environmental chemistry letters*, *20*(4), 2277-2310. https://doi.org/10.1007/s10311-022-01435-8

[26] Chen, W. J., Marcus, G. S., & Leesburg, D. S. (2021). Quantum computing for manufacturing and supply chain optimization: enhancing efficiency, reducing costs, and improving product quality. *International Journal of Enterprise Modelling*, *15*(3), 130-147. https://doi.org/10.35335/emod.v15i3.48

[27] Chithambo, L., Tingbani, I., Agyapong, G. A., Gyapong, E., & Damoah, I. S. (2020). Corporate voluntary greenhouse gas reporting: stakeholder pressure and the mediating role of the chief executive officer. *Business Strategy and the Environment*, *29*(4), 1666-1683. https://doi.org/10.1002/bse.2460

[28] Choi, T.-M., Kumar, S., Yue, X., & Chan, H.-L. (2022). Disruptive Technologies and Operations Management in the Industry 4.0 Era and Beyond. *Production and Operations Management*, *31*(1), 9-31. https://doi.org/10.1111/poms.13622

[29] Christidis, K., & Devetsikiotis, M. (2016). Blockchains and Smart Contracts for the Internet of Things. *IEEE Access*, *4*(NA), 2292-2303. https://doi.org/10.1109/access.2016.2566339

[30] Cong, C., Page, J., Kwak, Y., Deal, B., & Kalantari, Z. (2024). AI Analytics for Carbon-Neutral City Planning: A Systematic Review of Applications. *Urban Science*, *8*(3), 104. https://www.mdpi.com/2413-8851/8/3/104

[31] Cronin, J., Anandarajah, G., & Dessens, O. (2018). Climate change impacts on the energy system: a review of trends and gaps. *Climatic Change*, *151*(2), 79-93. https://doi.org/10.1007/s10584-018-2265-4

[32] Cruzes, D. S., Dybå, T., Runeson, P., & Höst, M. (2014). Case studies synthesis: a thematic, cross-case, and narrative synthesis worked example. *Empirical Software Engineering*, *20*(6), 1634-1665. https://doi.org/10.1007/s10664-014-9326-8

[33] Czeczot, G., Rojek, I., Mikołajewski, D., & Sangho, B. (2023). AI in IIoT Management of Cybersecurity for Industry 4.0 and Industry 5.0 Purposes. *Electronics*, *12*(18), 3800-3800. https://doi.org/10.3390/electronics12183800

[34] Dahlström, K., Howes, C., Leinster, P., & Skea, J. (2003). Environmental management systems and company performance: assessing the case for extending risk - based regulation. *European Environment*, *13*(4), 187-203. https://doi.org/10.1002/eet.323

[35] Danish, M. S. S. (2023). AI in Energy: Overcoming Unforeseen Obstacles. *AI*, *4*(2), 406-425. https://doi.org/10.3390/ai4020022

[36] Danish, M. S. S., & Senjyu, T. (2023). AI-Enabled Energy Policy for a Sustainable Future. *Sustainability*, *15*(9), 7643-7643. https://doi.org/10.3390/su15097643

[37] Dasgupta, A., & Islam, M. M., Nahid, Omar Faruq, Rahmatullah, Rafio, . (2024). Engineering Management Perspectives on Safety Culture in Chemical and Petrochemical Plants: A Systematic Review. *ACADEMIC JOURNAL ON SCIENCE, TECHNOLOGY, ENGINEERING & MATHEMATICS EDUCATION*, *1*(1), 10.69593.

[38] de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Sarkis, J., Gunasekaran, A., Alves, M. W. F. M., & Ribeiro, D. A. (2018). Decarbonisation of operations management–looking back, moving forward: a review and implications for the production research community. *International Journal of Production Research*, *57*(15-16), 4743-4765. https://doi.org/10.1080/00207543.2017.1421790

[39] Delgado, A., Casares, P. A. M., dos Reis, R., Zini, M. S., Campos, R., Cruz-Hernández, N., Voigt, A.-C., Lowe, A., Jahangiri, S., Martin-Delgado, M. A., Mueller, J. E., & Arrazola, J. M. (2022). Simulating key properties of lithium-ion batteries with a fault-tolerant quantum computer. *Physical Review A*, *106*(3), NA-NA. https://doi.org/10.1103/physreva.106.032428

[40] Desogus, G., Quaquero, E., Rubiu, G., Gatto, G., & Perra, C. (2021). BIM and IoT Sensors Integration: A Framework for Consumption and Indoor Conditions Data Monitoring of Existing Buildings. *Sustainability*, *13*(8), 4496-NA. https://doi.org/10.3390/su13084496

[41] Devaraj, J., Elavarasan, R. M., Shafiullah, G., Jamal, T., & Khan, I. (2021). A holistic review on energy forecasting using big data and deep learning models. *International Journal of Energy Research*, *45*(9), 13489-13530. https://doi.org/10.1002/er.6679

[42] Di Giorgio, A., & Liberati, F. (2014). Near real time load shifting control for residential electricity prosumers under designed and market indexed pricing models. *Applied Energy*, *128*(NA), 119-132. https://doi.org/10.1016/j.apenergy.2014.04.032

[43] Dorokhova, M., Vianin, J. E. N., Alder, J.-M., Ballif, C., Wyrsch, N., & Wannier, D. (2021). A Blockchain-Supported Framework for Charging Management of Electric Vehicles. *Energies*, *14*(21), 7144-NA. https://doi.org/10.3390/en14217144

[44] Downie, J., & Stubbs, W. (2012). Corporate Carbon Strategies and Greenhouse Gas Emission Assessments: The Implications of Scope 3 Emission Factor Selection. *Business Strategy and the Environment*, *21*(6), 412-422. https://doi.org/10.1002/bse.1734

[45] Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2021). Artificial Intelligence (AI) : Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(NA), 101994-NA. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[46] Eskandarpour, R., Gokhale, P., Khodaei, A., Chong, F. T., Passo, A., & Bahramirad, S. (2020). Quantum Computing for Enhancing Grid Security. *IEEE Transactions on Power Systems*, *35*(5), 4135-4137. https://doi.org/10.1109/tpwrs.2020.3004073

[47] Falekas, G., & Karlis, A. (2021). Digital Twin in Electrical Machine Control and Predictive Maintenance: State-of-the-Art and Future Prospects. *Energies*, *14*(18), 5933-NA. https://doi.org/10.3390/en14185933

[48] Fehr, E., & Gächter, S. (2002). Altruistic punishment in humans. *Nature*, *415*(6868), 137-140. https://doi.org/10.1038/415137a

[49] Fingerhuth, M., Babej, T., & Wittek, P. (2018). Open source software in quantum computing. *PloS one*, *13*(12), e0208561-NA. https://doi.org/10.1371/journal.pone.0208561

[50] Fombrun, C. J., & Foss, C. (2004). Business Ethics: Corporate Responses to Scandal. *Corporate Reputation Review*, *7*(3), 284-288. https://doi.org/10.1057/palgrave.crr.1540226

[51] Ford, R., & Hardy, J. (2020). Are we seeing clearly? The need for aligned vision and supporting strategies to deliver net-zero electricity systems. *Energy Policy*, *147*(NA), 111902-111902. https://doi.org/10.1016/j.enpol.2020.111902

[52] Ganesan, M., Kor, A.-L., Pattinson, C., & Rondeau, E. (2020). Green cloud software engineering for big data processing. *Sustainability*, *12*(21), 9255-NA. https://doi.org/10.3390/su12219255

[53] Gong, Y., Jia, F., Brown, S., & Koh, L. (2018). Supply chain learning of sustainability in multi-tier supply chains: A resource orchestration perspective. *International Journal of Operations & Production Management*, *38*(4), 1061-1090. https://doi.org/10.1108/ijopm-05-2017-0306

[54] Haque, F., & Ntim, C. G. (2022). Do corporate sustainability initiatives improve corporate carbon performance? Evidence from European firms. *Business Strategy and the Environment*, *31*(7), 3318-3334. https://doi.org/10.1002/bse.3078

[55] Hauser, O. P., Rand, D. G., Peysakhovich, A., & Nowak, M. A. (2014). Cooperating with the future. *Nature*, *511*(7508), 220-223. https://doi.org/10.1038/nature13530

[56] Heredge, J., Hill, C. D., Hollenberg, L. C. L., & Sevior, M. (2021). Quantum Support Vector Machines for Continuum Suppression in B Meson Decays. *Computing and Software for Big Science*, *5*(1), NA-NA. https://doi.org/10.1007/s41781-021-00075-x

[57] Hey, T. (1999). Quantum computing: an introduction. *Computing & Control Engineering Journal*, *10*(3), 105-112. https://doi.org/10.1049/cce:19990303

[58] Hossain, A., Khan, M. R., Islam, M. T., & Islam, K. S. (2024). Analyzing The Impact Of Combining Lean Six Sigma Methodologies With Sustainability Goals. *Journal of Science and Engineering Research*, *1*(01), 123-144. https://doi.org/10.70008/jeser.v1i01.57

[59] Hossain, M. R., Mahabub, S., & Das, B. C. (2024). The role of AI and data integration in enhancing data protection in US digital public health an empirical study. *Edelweiss Applied Science and Technology*, *8*(6), 8308-8321.

[60] Hua, W., Chen, Y., Qadrdan, M., Jiang, J., Sun, H., & Wu, J. (2022). Applications of blockchain and artificial intelligence technologies for enabling prosumers in smart grids: A review. *Renewable and Sustainable Energy Reviews*, *161*(NA), 112308-112308. https://doi.org/10.1016/j.rser.2022.112308

[61] Hua, W., Jiang, J., Sun, H., & Wu, J. (2020). A blockchain based peer-to-peer trading framework integrating energy and carbon markets. *Applied Energy*, *279*(NA), 115539-NA. https://doi.org/10.1016/j.apenergy.2020.115539

[62] Huang, Y. A., Weber, C. L., & Matthews, H. S. (2009). Categorization of Scope 3 emissions for streamlined enterprise carbon footprinting. *Environmental science & technology*, *43*(22), 8509-8515. https://doi.org/10.1021/es901643a

[63] Inderwildi, O. R., Zhang, C., Wang, X., & Kraft, M. (2020). The impact of intelligent cyber-physical systems on the decarbonization of energy. *Energy & Environmental Science*, *13*(3), 744-771. https://doi.org/10.1039/c9ee01919g

[64] Islam, M. M., Prodhan, R. K., Shohel, M. S. H., & Morshed, A. S. M. (2025). Robotics and Automation in Construction Management Review Focus: The application of robotics and automation technologies in construction. *Journal of Next-Gen Engineering Systems*, *2*(01), 48-71. https://doi.org/10.70937/jnes.v2i01.63

[65] Islam, M. M., Shofiullah, S., Sumi, S. S., & Shamim, C. M. A. H. (2024). Optimizing HVAC Efficiency And Reliability: A Review Of Management Strategies For Commercial And Industrial Buildings. *ACADEMIC JOURNAL ON SCIENCE, TECHNOLOGY, ENGINEERING & MATHEMATICS EDUCATION*, *4*(04), 74-89. https://doi.org/10.69593/ajsteme.v4i04.129

[66] Islam, M. T. (2024). A Systematic Literature Review On Building Resilient Supply Chains Through Circular Economy And Digital Twin Integration. *Frontiers in Applied Engineering and Technology*, *1*(01), 304-324. https://doi.org/10.70937/faet.v1i01.44

[67] Islam, M. T., Islam, K. S., Hossain, A., & Khan, M. R. (2025). Reducing Operational Costs in U.S. Hospitals Through Lean Healthcare And Simulation-Driven Process Optimization. *Journal of Next-Gen Engineering Systems*, *2*(01), 11-28. https://doi.org/10.70937/jnes.v2i01.50

[68] Jaber, M. Y., Glock, C. H., & Saadany, A. M. A. E. (2013). Supply chain coordination with emissions reduction incentives. *International Journal of Production Research*, *51*(1), 69-82. https://doi.org/10.1080/00207543.2011.651656

[69] Jaeger, F. A., Saling, P., Otte, N., Steidle, R., Bollen, J., Golembiewski, B., Dencic, I., Letinois, U., Rehl, T., & Wunderlich, J. (2022). Challenges and requirements of exchanging Product Carbon Footprint information in the supply chain. *E3S Web of Conferences*, *349*(NA), 7005-07005. https://doi.org/10.1051/e3sconf/202234907005

[70] Jahan, F. (2024). A Systematic Review Of Blue Carbon Potential in Coastal Marshlands: Opportunities For Climate Change Mitigation And Ecosystem Resilience. *Frontiers in Applied Engineering and Technology*, *2*(01), 40-57. https://doi.org/10.70937/faet.v2i01.52

[71] Jia, F., Gong, Y., & Brown, S. (2019). Multi-tier sustainable supply chain management: The role of supply chain leadership. *International Journal of Production Economics*, *217*(NA), 44-63. https://doi.org/10.1016/j.ijpe.2018.07.022

[72] Jim, M. M. I., Hasan, M., & Munira, M. S. K. (2024). The Role Of AI In Strengthening Data Privacy For Cloud Banking. *Frontiers in Applied Engineering and Technology*, *1*(01), 252-268. https://doi.org/10.70937/faet.v1i01.39

[73] Juszczyk, O., & Shahzad, K. (2022). Blockchain Technology for Renewable Energy: Principles, Applications and Prospects. *Energies*, *15*(13), 4603-4603. https://doi.org/10.3390/en15134603

[74] Koh, S. C. L., Genovese, A., Acquaye, A., Barratt, P., Rana, N., Kuylenstierna, J. C. I., & Gibbs, D. (2013). Decarbonising product supply chains: design and development of an integrated evidence-based decision support system – the supply chain environmental analysis tool (SCEnAT). *International Journal of Production Research*, *51*(7), 2092-2109. https://doi.org/10.1080/00207543.2012.705042

[75] Kontogiannis, D., Bargiotas, D., & Daskalopulu, A. (2020). Minutely Active Power Forecasting Models Using Neural Networks. *Sustainability*, *12*(8), 3177-NA. https://doi.org/10.3390/su12083177

[76] Kordzanganeh, M., Buchberger, M., Kyriacou, B., Povolotskii, M., Fischer, W., Kurkin, A., Somogyi, W., Sagingalieva, A., Pflitsch, M., & Melnikov, A. (2023). Benchmarking Simulated and Physical Quantum Processing Units Using Quantum and Hybrid Algorithms. *Advanced Quantum Technologies*, *6*(8), NA-NA. https://doi.org/10.1002/qute.202300043

[77] Kumar, M. A., Mohammed, A., Marimuthu, M., & Sundaravadivazhagan, B. (2025). Exploring the Entrepreneurial Opportunities Arising from AI‐Driven Quantum Computing Advancements. *Quantum Computing and Artificial Intelligence*, 497-522. https://doi.org/10.1002/9781394242399.ch19

[78] Lee, S.-Y. (2011). Corporate Carbon Strategies in Responding to Climate Change. *Business Strategy and the Environment*, *21*(1), 33-48. https://doi.org/10.1002/bse.711

[79] Lee, S.-Y., Klassen, R. D., Furlan, A., & Vinelli, A. (2014). The green bullwhip effect: Transferring environmental requirements along a supply chain. *International Journal of Production Economics*, *156*(NA), 39-51. https://doi.org/10.1016/j.ijpe.2014.05.010

[80] Lemma, T. T., Lulseged, A., & Tavakolifar, M. (2021). Corporate commitment to climate change action, carbon risk exposure, and a firm's debt financing policy. *Business Strategy and the Environment*, *30*(8), 3919-3936. https://doi.org/10.1002/bse.2849

[81] Lewandowski, S. (2017). Corporate Carbon and Financial Performance: The Role of Emission Reductions. *Business Strategy and the Environment*, *26*(8), 1196-1211. https://doi.org/10.1002/bse.1978

[82] Li, M., Wiedmann, T., & Hadjikakou, M. (2019). Enabling Full Supply Chain Corporate Responsibility: Scope 3 Emissions Targets for Ambitious Climate Change Mitigation. *Environmental science & technology*, *54*(1), 400-411. https://doi.org/10.1021/acs.est.9b05245

[83] Liu, L., Zhou, W., Guan, K., Peng, B., Xu, S., Tang, J., Zhu, Q., Till, J., Jia, X., Jiang, C., Wang, S., Qin, Z., Kong, H., Grant, R., Mezbahuddin, S., Kumar, V., & Jin, Z. (2024). Knowledge-guided machine learning can improve carbon cycle quantification in agroecosystems. *Nature communications*, *15*(1), 357. https://doi.org/10.1038/s41467-023-43860-5

[84] Lohachab, A., Lohachab, A., & Jangra, A. (2020). A comprehensive survey of prominent cryptographic aspects for securing communication in post-quantum IoT networks. *Internet of Things*, *9*(NA), 100174-NA. https://doi.org/10.1016/j.iot.2020.100174

[85] Lordi, V., & Nichol, J. M. (2021). Advances and opportunities in materials science for scalable quantum computing. *MRS Bulletin*, *46*(7), 589-595. https://doi.org/10.1557/s43577-021-00133-0

[86] Lyu, W., & Liu, J. (2021). Artificial Intelligence and emerging digital technologies in the energy sector. *Applied Energy*, *303*(NA), 117615-NA. https://doi.org/10.1016/j.apenergy.2021.117615

[87] Mahabub, S., Das, B. C., & Hossain, M. R. (2024). Advancing healthcare transformation: AI-driven precision medicine and scalable innovations through data analytics. *Edelweiss Applied Science and Technology*, *8*(6), 8322-8332.

[88] Mahabub, S., Jahan, I., Islam, M. N., & Das, B. C. (2024). The Impact of Wearable Technology on Health Monitoring: A Data-Driven Analysis with Real-World Case Studies and Innovations. *Journal of Electrical Systems*, *20*.

[89] Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40

[90] Manupati, V. K., Schoenherr, T., Ramkumar, M., Wagner, S. M., Pabba, S. K., & Singh, R. I. R. (2019). A blockchain-based approach for a multi-echelon sustainable supply chain. *International Journal of Production Research*, *58*(7), 2222-2241. https://doi.org/10.1080/00207543.2019.1683248

[91] Mastroianni, C., Plastina, F., Scarcello, L., Settino, J., & Vinci, A. (2024). Assessing Quantum Computing Performance for Energy Optimization in a Prosumer Community. *IEEE Transactions on Smart Grid*, *15*(1), 444-456. https://doi.org/10.1109/tsg.2023.3286106

[92] Matthews, H. S., Hendrickson, C., & Weber, C. L. (2008). The Importance of Carbon Footprint Estimation Boundaries. *Environmental science & technology*, *42*(16), 5839-5842. https://doi.org/10.1021/es703112w

[93] Mawson, V. J., & Hughes, B. R. (2020). Deep learning techniques for energy forecasting and condition monitoring in the manufacturing sector. *Energy and Buildings*, *217*(NA), 109966-NA. https://doi.org/10.1016/j.enbuild.2020.109966

[94] Mbuwir, B. V., Geysen, D., Spiessens, F., & Deconinck, G. (2019). Reinforcement learning for control of flexibility providers in a residential microgrid. *IET Smart Grid*, *3*(1), 98-107. https://doi.org/10.1049/iet-stg.2019.0196

[95] Md Mahfuj, H., Md Rabbi, K., Mohammad Samiul, I., Faria, J., & Md Jakaria, T. (2022). Hybrid Renewable Energy Systems: Integrating Solar, Wind, And Biomass for Enhanced Sustainability And Performance. *American Journal of Scholarly Research and Innovation*, *1*(1), 1-24. https://doi.org/10.63125/8052hp43

[96] Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[97] Mengelkamp, E., Notheisen, B., Beer, C., Dauer, D., & Weinhardt, C. (2017). A blockchain-based smart grid: towards sustainable local energy markets. *Computer Science - Research and Development*, *33*(1), 207-214. https://doi.org/10.1007/s00450-017-0360-9

[98] Morstyn, T., Teytelboym, A., & McCulloch, M. (2019). Bilateral Contract Networks for Peer-to-Peer Energy Trading. *IEEE Transactions on Smart Grid*, *10*(2), 2026-2035. https://doi.org/10.1109/tsg.2017.2786668

[99] Mridha Younus, S. H., amp, & Md Morshedul, I. (2024). Advanced Business Analytics in Textile & Fashion Industries: Driving Innovation And Sustainable Growth. *International Journal of Management Information Systems and Data Science*, *1*(2), 37-47. https://doi.org/10.62304/ijmisds.v1i2.143

[100] Mridha Younus, S. H. P. M. R. A. I. T., amp, & Rajae, O. (2024). Sustainable Fashion Analytics: Predicting The Future of Eco-Friendly Textile. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *3*(03), 13-26. https://doi.org/10.62304/jbedpm.v3i03.85

[101] Muhammad Mohiul, I., Morshed, A. S. M., Md Enamul, K., & Md, A.-A. (2022). Adaptive Control Of Resource Flow In Construction Projects Through Deep Reinforcement Learning: A Framework For Enhancing Project Performance In Complex Environments. *American Journal of Scholarly Research and Innovation*, *1*(01), 76-107. https://doi.org/10.63125/gm77xp11

[102] Munira, M. S. K. (2025). Digital Transformation in Banking: A Systematic Review Of Trends, Technologies, And Challenges. *Strategic Data Management and Innovation*, *2*(01), 78-95. https://doi.org/10.71292/sdmi.v2i01.12

[103] Nassef, A. M., Olabi, A. G., Rezk, H., & Abdelkareem, M. A. (2023). Application of Artificial Intelligence to Predict CO2 Emissions: Critical Step towards Sustainable Environment. *Sustainability*, *15*(9), 7648-7648. https://doi.org/10.3390/su15097648

[104] Nielsen, P., Johnston, S., & Black, P. (2021). Real time emissions monitoring: the foundation of a blockchain enabled carbon economy. *The APPEA Journal*, *61*(2), 450-453. https://doi.org/10.1071/aj20042

[105] Nordhaus, W. D. (2019). Climate Change: The Ultimate Challenge for Economics. *American Economic Review*, *109*(6), 1991-2014. https://doi.org/10.1257/aer.109.6.1991

[106] Omorogiuwa, E., & Ashiathah, I. (2021). Review of machine learning applications to power systems studies. *Open Access Research Journal of Engineering and Technology*, *1*(1), 21-31. https://doi.org/10.53022/oarjet.2021.1.1.0101

[107] Pan, Y., Zhang, X., Wang, Y., Yan, J., Zhou, S., Li, G., & Bao, J. (2019). Application of Blockchain in Carbon Trading. *Energy Procedia*, *158*(NA), 4286-4291. https://doi.org/10.1016/j.egypro.2019.01.509

[108] Parag, Y., & Sovacool, B. K. (2016). Electricity market design for the prosumer era. *Nature Energy*, *1*(4), 16032-NA. https://doi.org/10.1038/nenergy.2016.32

[109] Pérez-Castillo, R., Serrano, M. A., & Piattini, M. (2021). Software modernization to embrace quantum technology. *Advances in Engineering Software*, *151*(NA), 102933-NA. https://doi.org/10.1016/j.advengsoft.2020.102933

[110] Pinkse, J., & Busch, T. (2013). The Emergence of Corporate Carbon Norms: Strategic Directions and Managerial Implications. *Thunderbird International Business Review*, *55*(6), 633-645. https://doi.org/10.1002/tie.21580

[111] Popescu, S. M., Mansoor, S., Wani, O. A., Kumar, S. S., Sharma, V., Sharma, A., Arya, V. M., Kirkham, M. B., Hou, D., Bolan, N., & Chung, Y. S. (2024). Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. *Frontiers in Environmental Science*, *12*(NA), NA-NA. https://doi.org/10.3389/fenvs.2024.1336088

[112] Rahaman, T., Siddikui, A., Abid, A.-A., & Ahmed, Z. (2024). Exploring the Viability of Circular Economy in Wastewater Treatment Plants: Energy Recovery and Resource Reclamation. *Well Testing*, *33*(S2).

[113] Rajawat, A. S., Chauhan, C., Goyal, S. B., Bhaladhare, P. R., Rout, D., & Gaidhani, A. R. (2022). Utilization Of Renewable Energy For Industrial Applications Using Quantum Computing. *SSRN Electronic Journal*, *NA*(NA), NA-NA. https://doi.org/10.2139/ssrn.4187814

[114] Rieffel, E., & Polak, W. (2000). An introduction to quantum computing for non-physicists. *ACM Computing Surveys*, *32*(3), 300-335. https://doi.org/10.1145/367701.367709

[115] Rojek, I., Mroziński, A., Kotlarz, P., Macko, M., & Mikołajewski, D. (2023). AI-Based Computational Model in Sustainable Transformation of Energy Markets. *Energies*, *16*(24), 8059-8059. https://doi.org/10.3390/en16248059

[116] Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42

[117] Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2018). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, *57*(7), 2117-2135. https://doi.org/10.1080/00207543.2018.1533261

[118] Sabid, A. M., & Kamrul, H. M. (2024). Computational And Theoretical Analysis On The Single Proton Transfer Process In Adenine Base By Using DFT Theory And Thermodynamics. *IOSR Journal of Applied Chemistry*.

[119] Sharma, P. K., Kumar, N., & Park, J. H. (2020). Blockchain Technology Toward Green IoT: Opportunities and Challenges. *IEEE Network*, *34*(4), 263-269. https://doi.org/10.1109/mnet.001.1900526

[120] Siddiki, A., Al-Arafat, M., Arif, I., & Islam, M. R. (2024). Prisma Guided Review Of Ai Driven Automated Control Systems For Real Time Air Quality Monitoring In Smart Cities. *Journal of Machine Learning, Data Engineering and Data Science*, *1*(01), 147-162. https://doi.org/10.70008/jmldeds.v1i01.51

[121] Stahl, B. C., & Wright, D. (2018). Ethics and Privacy in AI and Big Data: Implementing Responsible Research and Innovation. *IEEE Security & Privacy*, *16*(3), 26-33. https://doi.org/10.1109/msp.2018.2701164

[122] Steane, A. M. (1999). Efficient fault-tolerant quantum computing. *Nature*, *399*(6732), 124-126. https://doi.org/10.1038/20127

[123] Sunny, M. A. U. (2024a). Eco-Friendly Approach: Affordable Bio-Crude Isolation from Faecal Sludge Liquefied Product. *Journal of Scientific and Engineering Research*, *11*(5), 18-25.

[124] Sunny, M. A. U. (2024b). Effects of Recycled Aggregate on the Mechanical Properties and Durability of Concrete: A Comparative Study. *Journal of Civil and Construction Engineering*, 7-14.

[125] Sunny, M. A. U. (2024c). Unveiling spatial insights: navigating the parameters of dynamic Geographic Information Systems (GIS) analysis. *International Journal of Science and Research Archive*, *11*(2), 1976-1985.

[126] Tajjour, S., & Chandel, S. S. (2023). Experimental investigation of a novel smart energy management system for performance enhancement of conventional solar photovoltaic microgrids. *Discover Energy*, *3*(1), NA-NA. https://doi.org/10.1007/s43937-023-00021-5

[127] Taufiqur, R. (2025). Smart Environmental Monitoring Systems For Air And Water Quality Management. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 1-19. https://doi.org/10.63125/a08zay47

[128] Tonoy, A. A. R., & Khan, M. R. (2023). The Role of Semiconducting Electrides In Mechanical Energy Conversion And Piezoelectric Applications: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(1), 01-23. https://doi.org/10.63125/patvqr38

[129] Tosun, J. (2022). Addressing climate change through climate action. *Climate Action*, *1*(1), NA-NA. https://doi.org/10.1007/s44168-022-00003-8

[130] Tyran, J.-R., & Feld, L. P. (2006). Achieving Compliance when Legal Sanctions are Non-Deterrent. *The Scandinavian Journal of Economics*, *108*(1), 135-156. https://doi.org/10.1111/j.1467-9442.2006.00444.x

[131] Ullo, S. L., & Sinha, G. R. (2020). Advances in Smart Environment Monitoring Systems Using IoT and Sensors. *Sensors*, *20*(11), 3113. https://www.mdpi.com/1424-8220/20/11/3113

[132] Waichman, I., Requate, T., Karde, M., & Milinski, M. (2021). Challenging conventional wisdom: Experimental evidence on heterogeneity and coordination in avoiding a collective catastrophic event. *Journal of Environmental Economics and Management*, *109*(NA), 102502-NA. https://doi.org/10.1016/j.jeem.2021.102502

[133] Wang, Y., Singgih, M., Wang, J., & Rit, M. (2019). Making sense of blockchain technology: How will it transform supply chains? *International Journal of Production Economics*, *211*(NA), 221-236. https://doi.org/10.1016/j.ijpe.2019.02.002

[134] Wu, T., & Wang, J. (2021). Artificial intelligence for operation and control: The case of microgrids. *The Electricity Journal*, *34*(1), 106890-NA. https://doi.org/10.1016/j.tej.2020.106890

[135] Xiao, H., Pei, W., Dong, Z., Kong, L., & Wang, D. (2018). Application and Comparison of Metaheuristic and New Metamodel Based Global Optimization Methods to the Optimal Operation of Active Distribution Networks. *Energies*, *11*(1), 85-NA. https://doi.org/10.3390/en11010085

[136] Younus, M. (2022). Reducing Carbon Emissions in The Fashion And Textile Industry Through Sustainable Practices and Recycling: A Path Towards A Circular, Low-Carbon Future. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 57-76. https://doi.org/10.62304/jbedpm.v1i1.226

[137] Younus, M. (2025). The Economics of A Zero-Waste Fashion Industry: Strategies To Reduce Wastage, Minimize Clothing Costs, And Maximize & Sustainability. *Strategic Data Management and Innovation*, *2*(01), 116-137. https://doi.org/10.71292/sdmi.v2i01.15

[138] Yu, W., Patros, P., Young, B., Klinac, E., & Walmsley, T. G. (2022). Energy digital twin technology for industrial energy management: Classification, challenges and future. *Renewable and Sustainable Energy Reviews*, *161*(NA), 112407-112407. https://doi.org/10.1016/j.rser.2022.112407

[139] Yuan, G., Gao, Y., Ye, B., & Liu, Z. (2021). A bilevel programming approach for real-time pricing strategy of smart grid considering multi-microgrids connection. *International Journal of Energy Research*, *45*(7), 10572-10589. https://doi.org/10.1002/er.6545

[140] Zaman, K., & Moemen, M. A.-e. (2017). Energy consumption, carbon dioxide emissions and economic development: Evaluating alternative and plausible environmental hypothesis for sustainable growth. *Renewable and Sustainable Energy Reviews*, *74*(NA), 1119-1130. https://doi.org/10.1016/j.rser.2017.02.072

[141] Zhang, A., Tay, H. L., Alvi, M. F., Wang, J. X., & Gong, Y. (2022). Carbon neutrality drivers and implications for firm performance and supply chain management. *Business Strategy and the Environment*, *32*(4), 1966-1980. https://doi.org/10.1002/bse.3230

[142] Zhang, D., Li, S., Sun, M., & O'Neill, Z. (2016). An Optimal and Learning-Based Demand Response and Home Energy Management System. *IEEE Transactions on Smart Grid*, *7*(4), 1790-1801. https://doi.org/10.1109/tsg.2016.2552169

[143] Zhang, Y., Pan, C.-L., & Liao, H.-T. (2021). Carbon Neutrality Policies and Technologies: A Scientometric Analysis of Social Science Disciplines. *Frontiers in Environmental Science*, *9*(NA), NA-NA. https://doi.org/10.3389/fenvs.2021.761736

[144] Zhao, Z., Jiexiong, Z., Yan, B., Runting, C., Lai, C. S., Huang, L., Guan, Q., & Lai, L. L. (2020). Decentralized Finite Control Set Model Predictive Control Strategy of Microgrids for Unbalanced and Harmonic Power Management. *IEEE Access*, *8*(NA), 202298-202311. https://doi.org/10.1109/access.2020.3034947

[145] Zhu, Y., & Yu, K. (2023). Artificial intelligence (AI) for quantum and quantum for AI. *Optical and Quantum Electronics*, *55*(8), NA-NA. https://doi.org/10.1007/s11082-023-04914-6