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# AGILE AND SUSTAINABLE SUPPLY CHAIN MANAGEMENT THROUGH AI-BASED PREDICTIVE ANALYTICS AND DIGITAL TWIN SIMULATION

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**Abstract**

This study addresses the practical problem of how global supply chains can become both agile and sustainable while adopting advanced digital technologies such as AI based predictive analytics and digital twin simulation. The purpose is to examine whether and how these capabilities improve supply chain agility, sustainable supply chain performance and overall supply chain performance in real cloud enabled and enterprise level cases. A quantitative, cross sectional, case-based survey design was applied, using Likert 5-point scales with data from 214 professionals (82.3 percent usable response rate) drawn from supply chain intensive manufacturing, logistics and retail organizations. Key variables included AI based predictive analytics capability, digital twin simulation capability, supply chain agility, sustainable supply chain performance and overall supply chain performance. The analysis plan comprised descriptive statistics, reliability testing, correlation analysis, multiple regression and bootstrapped mediation tests. Results show that AI capability ($\beta = 0.42$, $p < 0.001$) and digital twin capability ($\beta = 0.29$, $p < 0.001$) together explain 46.3 percent of the variance in agility, and 41.7 percent of variance in sustainable performance, while the full performance model explains 58.9 percent of the variance in overall supply chain performance. Agility ($\beta = 0.31$) and sustainability ($\beta = 0.28$) partially mediate the effects of AI and digital twin capabilities, confirming that digital investments translate into superior performance largely through agile and sustainability-oriented practices. The findings imply that managers should treat AI analytics and digital twins as strategic, end to end capabilities for building agile, sustainable and competitively resilient digital supply chains.

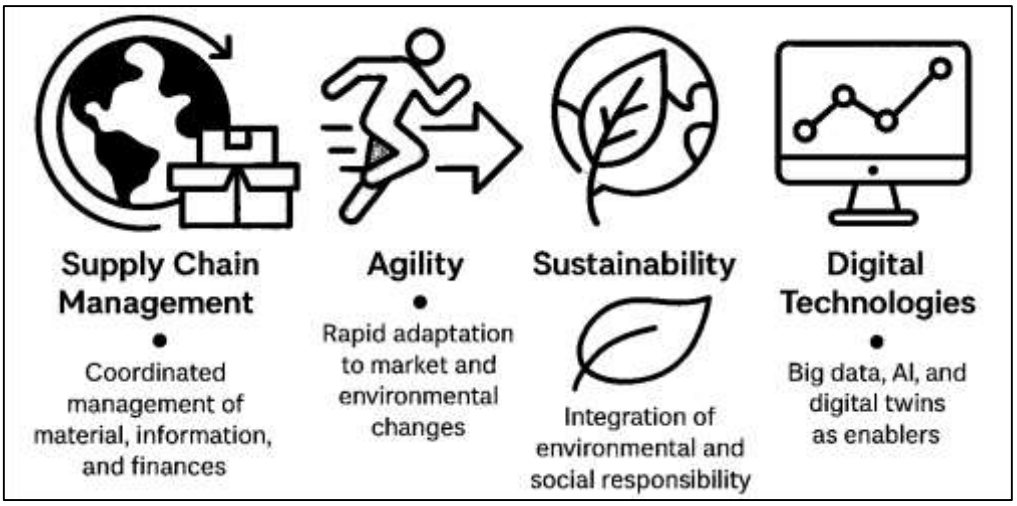
**Keywords**

*AI Based Predictive Analytics Capability; Digital Twin Simulation; Supply Chain Agility; Sustainable Supply Chain Performance; Digital Supply Chain Performance;*

## INTRODUCTION

Supply chain management (SCM) is commonly defined as the coordinated management of flows of materials, information, and finances across suppliers, manufacturers, logistics providers, and customers to create value at minimum total cost and risk. From the mid-2000s onward, scholars have emphasized that global supply chains operate as complex, interdependent networks exposed to cost pressure, environmental regulation, and uncertainty, so that traditional efficiency-only models are no longer sufficient (Linton et al., 2007). Sustainable supply chain management extends SCM by explicitly integrating environmental and social performance alongside economic outcomes, often framed as the triple bottom line (Carter & Rogers, 2008). In parallel, the concept of supply chain agility has emerged as a strategic capability that enables rapid sensing and response to market changes and disruptions through flexible processes, collaborative relationships, and timely information sharing (Schoenherr & Speier-Pero, 2015). Recent work stresses that agility and sustainability are no longer optional; they underpin competitiveness in international supply chains that must simultaneously meet service expectations, cost targets, and stringent environmental and social norms (Dubey et al., 2017). Against this background, the present research focuses on agile and sustainable supply chain management as intertwined strategic logics rather than isolated priorities.

**Figure 1: Foundations of Modern Supply Chain Management**




The push toward agility arises from the escalating volatility of demand, shorter product life cycles, and geographically dispersed sourcing, all of which increase exposure to supplier failures, quality incidents, and macro-level shocks. Empirical studies identify agility as a higher-order dynamic capability supported by modular processes, postponement, and collaborative planning, which enable rapid reconfiguration of supply, manufacturing, and distribution activities (Swafford et al., 2006). Logistics capabilities such as real-time transport visibility, responsive warehousing, and synchronized information flows have been shown to be critical antecedents of agility and are positively associated with service performance and customer satisfaction (Singh & El-Kassar, 2019). At the same time, sustainability-oriented regulations and stakeholder pressures require supply chains to reduce carbon emissions, manage hazardous materials, and ensure fair labor practices across global tiers (Liu et al., 2013). Sustainable SCM research has progressively moved from compliance and "green" initiatives toward integrated frameworks that link environmental and social investments to risk reduction, reputation, and long-term competitiveness (Lu et al., 2020). More recent empirical work suggests that sustainable practices can be embedded in dynamic supply chain capabilities, so that firms with strong sustainability routines exhibit better responsiveness and performance under turbulence (Marmolejo-Saucedo, 2020). Thus, the international debate is shifting from whether agile and sustainable supply chains are needed to how they can be designed and governed coherently.

Parallel to these strategic developments, the digitalization of supply chains has generated unprecedented volumes of operational and contextual data, giving rise to big data analytics and AI-

based predictive analytics as key enablers of data-driven decision-making. Big data in supply chains typically exhibit high volume, velocity, and variety, arising from sources such as RFID tags, sensors, GPS traces, social media, transactional systems, and external market feeds (Melesse et al., 2020). Data science and predictive analytics combine statistical learning, optimization, and machine learning to detect patterns and generate predictions about demand, lead times, failure probabilities, and other key metrics (Seuring & Müller, 2008). From a resource-based and dynamic capabilities perspective, such analytics capabilities are viewed as intangible, hard-to-imitate resources that can enhance supply chain performance when embedded in processes and routines (Waller & Fawcett, 2013). Empirical studies show that organizations which assimilate big data and predictive analytics into their supply chain decisions tend to achieve superior visibility, coordination, and responsiveness compared to less data-driven competitors (Abdulla & Ibne, 2021; Wang et al., 2016). At the same time, researchers highlight that the value of analytics depends critically on data quality, governance, and alignment with strategic objectives, since poor data or misaligned algorithms can degrade rather than improve operational decisions (Tiwari et al., 2018).

AI-enabled predictive analytics are increasingly examined in relation to both agility and sustainability outcomes in supply chains. On the agility side, big data and predictive models support finer-grained demand sensing, dynamic safety stock optimization, and proactive identification of potential bottlenecks or disruptions, thereby reducing response times and allowing more flexible fulfillment strategies (Ferdous Ara, 2021; Yu et al., 2017). On the sustainability side, analytics are applied to monitor emissions, energy consumption, and waste across facilities and transport networks, enabling firms to redesign routes, production schedules, and sourcing portfolios to reduce environmental impact (Habibullah & Foysal, 2021; Srivastava, 2007). Theories linking big data and sustainability argue that predictive analytics can address informational asymmetries between firms and stakeholders, enhance transparency, and support more credible environmental and social performance claims (Ding, 2019; Md Sarwar, 2021). Literature reviews of big data analytics in logistics and SCM indicate rapid growth of applications in forecasting, network design, inventory optimization, and risk management, but also note that many organizations struggle to convert pilot projects into scalable capabilities that consistently enhance supply chain performance (Gligor & Holcomb, 2012; Musfiqur & Saba, 2021). Overall, the evidence suggests that AI-driven predictive analytics can be a powerful enabler of both agile and sustainable supply chains, provided that they are embedded in coherent process architectures and governance structures.

More recently, the digital twin concept has emerged as a complementary technological paradigm for data-driven supply chain management (Redwanul et al., 2021). A digital twin is typically defined as a virtual representation of a physical asset, process, or system that is updated with real-time data and can be used to understand, analyze, and predict its behavior (Wamba et al., 2018; Reza et al., 2021). In manufacturing contexts, digital twin-driven smart factories integrate cyber-physical systems, sensors, and simulation models to mirror machines, lines, or entire plants, providing a basis for monitoring, diagnosis, and predictive maintenance (Gunasekaran et al., 2017; Saikat, 2021). Systematic reviews show that digital twin models in industrial operations are increasingly employed to study throughput, bottlenecks, and reliability, using both static and dynamic simulations linked to real-time data streams (Hazen et al., 2014; Shaikh & Aditya, 2021). In logistics and supply chain settings, digital twins have been conceptualized as virtual replicas of warehouses, transport networks, or end-to-end supply chains, enabling managers to experiment with alternative configurations and operating policies under realistic constraints (Hazen et al., 2016; Amin, 2022). Early case studies suggest that supply chain digital twins can support better synchronization of material and information flows, reduce uncertainties, and improve service levels by allowing continuous scenario analysis and optimization in a virtual environment before changes are implemented physically (Büyüközkan & Göçer, 2018; Ariful, 2022). As digital twin technologies mature, they are increasingly combined with big data and AI algorithms to enhance their predictive and prescriptive capabilities, creating rich testbeds for complex decision-making in global supply networks (Hong et al., 2018; Ariful & Ara, 2022).

The broader notion of the digital supply chain provides an integrating umbrella for these technologies. A digital supply chain is described as a smart, value-driven, and data-intensive configuration in which

physical flows are orchestrated through advanced information technologies, analytics, and automation, rather than purely transactional coordination (Agarwal et al., 2007; Nahid, 2022). Digital supply chain frameworks highlight enablers such as cloud computing, Internet of Things (IoT), advanced analytics, and cyber-physical systems, and emphasize stages of digital strategy, technology implementation, and digitally enabled supply chain management (Hossain & Milon, 2022; Swafford et al., 2006). Within this architecture, AI-based predictive analytics and digital twins function as complementary components: predictive models extract patterns and forecasts from large data sets, while digital twins provide immersive simulation environments that can embed those predictions into operational planning, scheduling, and risk analysis (Lu et al., 2020; Mominul et al., 2022). Studies of big data and predictive analytics in logistics and supply chain management show that digital supply chains can achieve higher transparency and coordination, particularly when analytics capabilities are tightly linked to cross-functional decision processes (Mortuza & Rauf, 2022; Wang et al., 2016). At the same time, research on digital twins in supply chains suggests that virtualized models can represent multi-echelon structures, lead times, and stochastic disturbances, offering a platform for testing agility-enhancing strategies such as capacity reallocation, dynamic routing, and multi-sourcing before real-world implementation (Rakibul & Samia, 2022; Tiwari et al., 2018).

Although the literatures on agility, sustainability, predictive analytics, and digital twins have grown substantially, empirical integration across these domains remains limited. Sustainable SCM research offers conceptual and theoretical frameworks such as triple-bottom-line-based models and conceptual process maps for sustainable supply chains but relatively few studies operationalize agility and sustainability jointly using quantitative measures linked to advanced digital technologies (Carter & Rogers, 2008; Saikat, 2022). Research on big data analytics and predictive analytics capability has mainly examined direct relationships with supply chain performance or firm-level outcomes, often focusing on technology assimilation, connectivity, and information sharing within a resource-based view (Tonoy Kanti & Shaikat, 2022; Yu et al., 2017). Meanwhile, emerging work on digital twin-driven manufacturing and supply chains has concentrated on technical architectures, modeling approaches, and proof-of-concept implementations, with limited quantitative analysis of organizational performance impacts (Arfan et al., 2023; Lu et al., 2020). There is also a relative scarcity of studies that explicitly connect AI-based predictive analytics and digital twin simulation with measurable indicators of supply chain agility (e.g., response time, flexibility) and sustainability (e.g., environmental and social performance) within the same empirical framework (Ara & Beatrice Onyinyechi, 2023; Mushfequr & Ashraful, 2023).

Within this evolving landscape, the present study focuses on the international significance of integrating AI-based predictive analytics and digital twin simulation into agile and sustainable supply chain management. From a dynamic capabilities and resource-based perspective, IT capabilities, analytics capabilities, and digital twin capabilities can be viewed as interrelated resources that shape sensing, seizing, and reconfiguring processes along the supply chain (Hazen et al., 2014). By examining how these capabilities are implemented in real organizational settings, and how they relate to observed agility and sustainability outcomes, it becomes possible to clarify the mechanisms through which data-driven technologies support or hinder strategic supply chain objectives. Existing evidence suggests that data quality, analytics assimilation, and managerial commitment are crucial for realizing the potential of predictive analytics in both economic and sustainability dimensions (Hazen et al., 2016). At the same time, case studies of digital supply chains and digital twin–enabled operations point to the importance of aligning virtual models with actual process constraints and decision rights (Lu et al., 2020; Marmolejo-Saucedo, 2020). Building on these insights, this research adopts a quantitative, cross-sectional, case-study–based design using Likert-type measures to investigate the relationships among AI-based predictive analytics capability, digital twin simulation capability, agile supply chain practices, and sustainable supply chain performance in an international business context.

The objective of this study is to systematically examine how AI-based predictive analytics and digital twin simulation contribute to agile and sustainable supply chain management and, in turn, to overall supply chain performance in an international business context. Specifically, the research seeks to operationalize AI-based predictive analytics capability and digital twin simulation capability as

measurable constructs and to assess their direct relationships with key dimensions of supply chain agility and sustainability performance. Building on this, the study aims to evaluate whether agile practices, such as responsiveness, flexibility, and rapid reconfiguration, and sustainability practices, such as resource efficiency, emissions reduction, and social responsibility, act as mediating mechanisms through which digital capabilities influence broader performance outcomes, including cost efficiency, service reliability, and resilience. The study further intends to develop and empirically test a conceptual model that links these technological and operational constructs using a quantitative, cross-sectional, case-study–based survey design. To achieve this, a structured questionnaire with Likert's five-point scale will be administered to supply chain, operations, and technology professionals within selected case organizations to capture their perceptions of AI analytics use, digital twin deployment, agility, sustainability, and performance. The collected data will be analyzed using descriptive statistics to profile the sample and summarize construct levels, correlation analysis to explore the strength and direction of associations among variables, and regression modeling to test the proposed hypotheses concerning direct and indirect effects. By framing the study around clearly defined objectives and a rigorously specified empirical model, the research focuses on clarifying which aspects of AI-based predictive analytics and digital twin simulation are most strongly associated with agile and sustainable supply chain outcomes, how these associations manifest within real organizational settings, and to what extent they translate into measurable performance advantages across the supply chain.

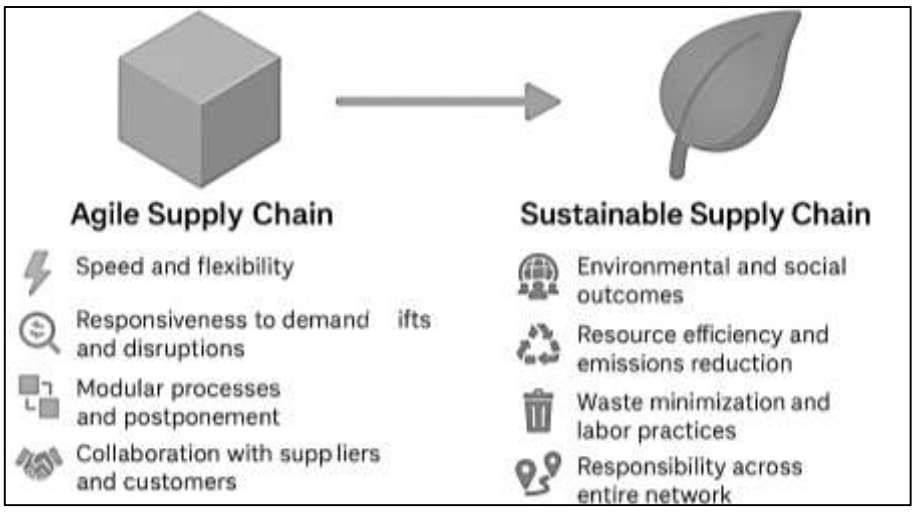
## LITERATURE REVIEW

The literature on supply chain management has evolved from viewing supply chains primarily as cost-efficient, linear pipelines to understanding them as complex, digitally enabled networks that must be simultaneously agile, sustainable, and resilient. Early work on agility and sustainability emphasized them as separate paradigms agility focusing on responsiveness, flexibility, and speed under demand uncertainty, and sustainability centering on environmental and social performance alongside economic viability yet more recent reviews argue that these logics increasingly intersect in practice and must be integrated conceptually (Carter & Rogers, 2008). Studies on agile–sustainable or "LARGS" (lean, agile, resilient, green, sustainable) supply chains show that common practices such as collaborative planning, modular process design, and real-time information sharing can simultaneously support responsiveness and triple-bottom-line outcomes when they are embedded in coherent supply chain strategies (Hasan & Rakibul, 2024; Shahrin & Samia, 2023). In parallel, a fast-growing body of work examines the role of artificial intelligence and predictive analytics in enabling data-driven decision-making across planning, sourcing, production, and logistics. AI-based predictive analytics exploit large, heterogeneous data sets to generate forecasts, risk scores, and scenario evaluations that can reduce uncertainty, improve demand–supply matching, and support proactive disruption management, thereby underpinning agility and resilience in increasingly volatile environments. At the same time, research on digital twin technology introduces the notion of virtual replicas of assets, processes, or end-to-end supply chains that are continuously synchronized with real-time data and used for monitoring, simulation, and optimization. Systematic reviews of digital twins for supply chains indicate that, although applications remain at a relatively early stage, digital twins can provide a powerful environment for testing configuration changes, evaluating risk mitigation strategies, and supporting performance improvements before interventions are implemented in the physical system. More recent integrative work on artificial intelligence in supply chain management suggests that AI, predictive analytics, and digital twins are converging within broader digital supply chain architectures, yet empirical research that jointly examines their impacts on agility, sustainability, and overall supply chain performance remains limited and fragmented (Büyüközkan & Göçer, 2018). Against this backdrop, the present literature review is structured to synthesize prior studies on agile and sustainable supply chain management, AI-based predictive analytics, and digital twin simulation, to clarify their conceptual linkages, and to identify theoretical and empirical gaps that motivate the development of an integrated model for agile and sustainable supply chain management through AI-based predictive analytics and digital twin simulation.

**Agile and Sustainable Supply Chain Management**

Agile and sustainable supply chain management has emerged as a response to the increasing volatility of global markets and the intensifying environmental and social expectations placed on firms. The agile supply chain concept emphasizes speed, flexibility, and responsiveness in managing flows of materials, information, and capital across networked organizations, allowing firms to sense and react quickly to demand shifts, disruptions, and customization needs. Rather than relying on rigid, efficiency-oriented configurations, agile supply chains are characterized by modular processes, postponement strategies, and close collaboration with suppliers and customers that together enable rapid reconfiguration of sourcing, production, and distribution activities. From a performance perspective, agility has been associated with shorter lead times, higher delivery reliability, and the capacity to handle product variety without excessive cost escalation. At the same time, sustainable supply chain management extends the focus beyond traditional economic metrics to include environmental and social outcomes along the upstream and downstream stages of the chain. Scholars distinguish sustainable supply chain management from narrower notions of green purchasing or end-of-pipe pollution control by its broad concern with resource efficiency, emissions reduction, waste minimization, labor conditions, and community impacts embedded in supply chain decisions. In such contexts, supply chain design choices regarding facility location, transportation modes, inventory positioning, and supplier selection must be evaluated through both agility and sustainability lenses. Multisourcing and regional sourcing, for instance, can enhance responsiveness while reducing dependence on long and carbon-intensive routes. Likewise, collaborative planning and information sharing increase visibility, enabling firms to synchronize supply with demand and to monitor environmental indicators across partners in a more integrated way. Together, these perspectives position agile and sustainable supply chain management as a holistic approach to structuring networks that are both competitively responsive and responsible in their broader impacts.

**Figure 2: Agile and Sustainable Supply Chain Management**




While the terms "green" and "sustainable" supply chain management are sometimes used interchangeably, the sustainability perspective is generally understood to encompass a more comprehensive integration of environmental and social issues alongside economic performance. Conceptual analyses of the field highlight that sustainable supply chain management involves the management of material, information, and capital flows in ways that align with long-term business viability and with broader societal goals such as climate change mitigation, resource conservation, and social equity (Beske & Seuring, 2014). A key insight from this body of work is that sustainability cannot be treated as an add-on to conventional purchasing and logistics policies, but must be embedded in governance structures, performance measurement systems, and strategic relationships across the chain. This includes the development of explicit criteria and indicators for assessing suppliers, logistics providers, and internal operations on dimensions such as energy efficiency, emissions intensity, waste

generation, occupational health and safety, and community impacts embedded in supply chain decisions. It also entails the design of incentive and monitoring mechanisms that encourage partners to invest in cleaner technologies and more socially responsible practices, thereby shaping the overall sustainability profile of the network rather than individual firms in isolation. In parallel, research has mapped the main categories of sustainable supply chain practices that firms deploy, including sustainable sourcing, green manufacturing, eco-efficient logistics, reverse flows, and closed-loop designs. These practices vary in ambition: some remain largely compliance-driven and oriented toward meeting regulatory thresholds, whereas others reflect more proactive strategies that use sustainability to support innovation, differentiation, and long-term competitiveness. A further strand of work links sustainability to risk management, arguing that environmental and social issues can materialize as operational disruptions, reputational damage, or market access barriers when not properly governed. This literature provides an important foundation for analyzing how digital technologies such as AI-based predictive analytics and digital twin simulation may reinforce, transform, or newly enable sustainable and agile supply chain configurations.

A growing stream of studies connects agile and sustainable supply chain management with underlying organizational capabilities and network relationships, suggesting that performance outcomes depend not only on the presence of individual practices but also on how they are configured and coordinated. From this perspective, agility is viewed as a dynamic capability that rests on the ability to sense changes in the environment, seize emerging opportunities, and reconfigure resources and processes across the supply chain in a timely manner. These capabilities are often underpinned by close collaboration with key suppliers and customers, high levels of information sharing, and the strategic use of flexible production and logistics assets. At the same time, sustainable supply chain management is increasingly conceptualized as a systemic capability that requires alignment between corporate sustainability strategies, supply chain structures, and partner selection and development processes, rather than a collection of isolated projects or tools. Such alignment shapes how quickly and effectively firms can translate sustainability goals into concrete operational changes in sourcing, production, and distribution. Recent work also highlights the relevance of resilience and robustness as complementary outcomes of agile and sustainable supply chains, particularly in contexts characterized by frequent disruptions, regulatory uncertainty, and stakeholder scrutiny (Brandon-Jones et al., 2014). Resilient supply chains are able to absorb shocks and recover performance through redundancy, flexibility, and adaptiveness, while robust structures maintain acceptable performance across a range of plausible scenarios without continuous reconfiguration. Integrating agility, sustainability, resilience, and robustness require firms to develop portfolios of capabilities that span structural decisions, such as network design and supplier base configuration, and relational mechanisms, such as joint planning, knowledge sharing, and collaborative innovation. In this integrated view, agile and sustainable supply chain management is not merely a set of operational techniques, but a multidimensional capability system that shapes how firms respond to turbulence, meet sustainability expectations, and compete in global markets. This systems orientation is particularly pertinent when considering the role of advanced digital technologies, which can both enable and constrain the ways in which agility and sustainability are realized in practice.

**AI-Based Predictive Analytics in Supply Chain Decision-Making**

AI-based predictive analytics in supply chain management refers to the systematic use of statistical learning, machine learning, and data mining techniques to transform historical and real-time data into forward-looking insights that support planning, coordination, and control decisions across the chain. Conceptually, predictive analytics extends traditional reporting and descriptive analytics by estimating the probability and magnitude of future outcomes such as demand levels, lead times, failure rates, or disruption events, and thus allows decision makers to anticipate and proactively adjust operations. Early empirical work on analytics in supply chains showed that the presence of advanced analytical capabilities in core processes plan, source, make, and deliver was significantly associated with improved supply chain performance, especially when supported by robust information systems and business process orientation (Trkman et al., 2010). Subsequent research on big data analytics capability argued that competitive advantage does not stem from data volumes alone, but from the firm's ability to assemble, integrate, and deploy specialized resources such as skilled personnel, scalable

infrastructure, and data management routines into a coherent analytics capability that rivals find difficult to imitate (Gupta & George, 2016). Within supply chain contexts, this capability perspective is critical because decision processes are distributed across multiple organizations, data sources are heterogeneous and noisy, and the value of predictions depends on how well they are embedded in planning and execution routines. Reviews of big data applications in operations and supply-chain management further highlight that predictive analytics is increasingly positioned as a central element of "data-driven" supply chains, where data streams from transactional systems, sensors, and external sources are continuously exploited to refine forecasts, detect anomalies, and optimize flows (Addo-Tenkorang & Helo, 2016).

**Figure 3: AI-Based Predictive Analytics in Supply Chain Decision-Making**




Building on these conceptual developments, more recent work adopts a capabilities-based lens to unpack how data-driven supply chains leverage predictive analytics for improved performance. One line of research focuses on big data analytics capability at the firm level, defining it as a higher-order construct that encompasses technological resources (platforms, tools), human skills (data science, domain expertise), and organizational processes (governance, decision integration) that together enable the generation and exploitation of predictive insights (Gupta & George, 2016). In a supply chain–specific context, this view has been extended to examine big data analytics capabilities in areas such as logistics, transportation, and sourcing, where the complexity and uncertainty of decisions makes predictive models particularly valuable. For example, a detailed literature review of big data applications in operations and supply-chain management documents how analytics has been used for demand forecasting, inventory optimization, routing, and capacity planning, and proposes a value-adding framework linking data sources, analytics methods, and decision domains (Addo-Tenkorang & Helo, 2016). Complementing these broad reviews, conceptual and empirical work on big data analytics capabilities in supply chain management explores the issues and challenges associated with implementing predictive analytics in practice, including data quality problems, skills shortages, misalignment between analytics initiatives and business strategy, and the difficulty of integrating

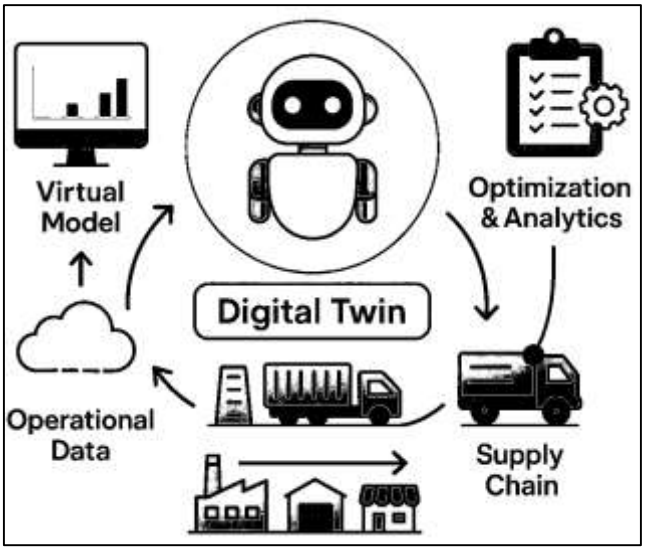
insights into existing planning processes (Arunachalam et al., 2018). This stream emphasizes that, in supply chain settings, predictive analytics must be understood not just as algorithms, but as socio-technical systems involving cross-functional collaboration, iterative model refinement, and continuous learning across organizational boundaries.

At the application level, AI-based predictive analytics is increasingly used to support concrete supply chain decisions, particularly those related to performance management, risk management, and proactive control. One influential study proposes a predictive supply chain performance management model that combines process modelling, performance measurement, data mining models, and web-based portals, allowing managers to simulate the impact of different decisions on key performance indicators and to act before undesirable trends manifest in the physical chain (Stefanovic, 2014). Such models illustrate how predictive analytics can shift supply chains from reactive performance reporting to proactive performance steering. In parallel, empirical research on analytics and supply chain performance shows that firms with more advanced analytical capabilities tend to achieve higher levels of delivery reliability, cost efficiency, and responsiveness, as predictive models help them better align supply with demand and adjust to volatility (Trkman et al., 2010). Descriptive and conceptual studies further map how big data and predictive analytics are being deployed across different stages of the supply chain, including procurement, production, logistics, and after-sales services, and how these deployments create new opportunities for integrated planning and cross-organizational coordination (Stefanovic, 2014). At the same time, capability-oriented analyses underline that realizing these benefits requires firms to systematically develop big data analytics capabilities, rather than adopting isolated tools or pilot projects (Gupta & George, 2016). Together, this body of work positions AI-based predictive analytics as a core enabler of data-driven supply chain decision-making, while also pointing to the importance of understanding how such capabilities interact with broader supply chain structures, processes, and strategic objectives.

**Digital Twin Simulation for Supply Chain Visibility**

Digital twin simulation has emerged as a central enabler of smart, data-driven supply chains because it provides a high-fidelity virtual representation of physical assets, processes, and networks that is continuously synchronized with operational data. Closely related to the notion of cyber-physical production systems, digital twins rely on embedded sensing, connectivity, and computation to couple the cyber and physical domains so that models reflect the evolving state of machines, factories, and logistics systems in near real time (Monostori, 2014).

**Figure 4: Data-Driven Digital Twin Framework for Enhancing Supply Chain Decision-Making**




Rather than being static planning tools, digital twins ingest data from enterprise applications, Internet of Things (IoT) devices, and external information sources, update their parameters, and then feedback

predictions and recommendations to decision makers. For supply chains, this means that virtual models of sourcing networks, production lines, distribution centers, and transport fleets can be used to explore scenarios such as demand surges, capacity shifts, regulatory changes, or disruption events without interrupting ongoing operations. The same models support continuous performance tracking and exception management, because deviations between observed and simulated behavior can be detected rapidly and used to trigger corrective actions or re-planning. By embedding optimization and analytics components into the twin, organizations can iteratively test alternative configurations such as changes in lot sizes, routing policies, or inventory thresholds and evaluate their impacts on cost, service, and risk profiles before implementation. The resulting feedback loop between data, models, and decisions is particularly valuable in environments characterized by volatility, customization, and sustainability pressures, where traditional deterministic planning approaches struggle to capture complex interactions between upstream and downstream actors. In this sense, digital twin simulation provides a foundational mechanism for aligning day-to-day operational choices with strategic goals related to agility, resilience, and efficient resource use, while maintaining a system-level view of the end-to-end supply chain.

Prior work on simulation-based decision support in supply chains provides an important bridge between traditional planning tools and fully fledged digital twins. Simulation and optimization models have long been used to evaluate inventory policies, facility locations, production schedules, and transportation strategies under uncertainty, but early implementations were typically run offline, based on static assumptions, and applied to relatively narrow segments of the network (Brinza, 2012). As global supply chains became more complex, researchers demonstrated that discrete-event and system-dynamics simulations could be combined with heuristic or mathematical optimization to analyze performance under alternative configurations and to identify robust policies for capacity allocation, lot sizing, and routing. These approaches made it possible to capture non-linear interactions, feedback loops, and stochastic effects that are difficult to represent in closed-form analytical models, thereby yielding deeper insights into bottlenecks, bullwhip effects, and trade-offs between cost, responsiveness, and risk. At the same time, advances in computational power and modeling environments reduced the time and expertise required to build and run detailed simulations, encouraging their application in real-world case studies across manufacturing, retail, and logistics. In many of these studies, simulation acts as a virtual laboratory in which decision makers can experiment with new process designs, coordination mechanisms, or technology investments without disrupting operations, thereby lowering the perceived risk of innovation. More recent work emphasizes linking simulation engines with real-time data feeds from enterprise resource planning, warehouse management, and transportation management systems so that model parameters, demand patterns, and disruption signals are updated automatically. This gradual convergence between data-rich simulation models and operational information systems sets the stage for digital twin solutions that remain continuously aligned with the physical supply chain and can support both strategic and operational decision-making.

Recent contributions explicitly position digital twin and virtual supply chain concepts as architectural solutions for enhancing supply chain visibility and decision quality. Coelho, Relvas, and Barbosa-(Matsuda et al., 2020) develop a simulation-based decision support tool for in-house logistics that models material flows and handling activities within distribution and production facilities, framing this tool as the foundational layer of a logistics digital twin. Their work demonstrates how operational data can be embedded in the simulation, how indicators such as utilization, lead time, and congestion can be monitored continuously, and how alternative layout or policy changes can be evaluated before implementation, thereby reducing risk and accelerating improvement cycles. At the network level, Matsuda and co-authors present a method for constructing virtual supply chains using enterprise e-catalogues, where standardized models of manufacturers, suppliers, and retailers are combined into a multi-agent system that represents the structural and behavioral characteristics of a real supply network (Matsuda et al., 2020). Building on this idea, Nishi et al. (2020) describe an automatic construction method in which software agents are generated directly from enterprise models and then connected to form a dynamic, multi-agent representation of the end-to-end chain. In this architecture, enterprise agents encapsulate both structural attributes, such as capacity and lead times, and decision

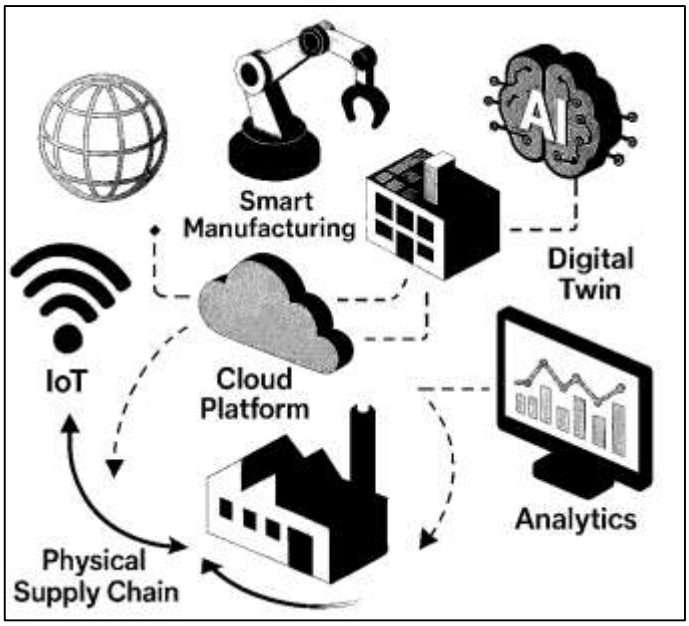
rules, such as ordering policies or negotiation strategies, allowing analysts to study how local decisions propagate through the network and influence global performance. When such virtual supply chains are linked with optimization and analytics modules, they effectively operate as digital twins that can be used to test "what-if" scenarios related to demand shifts, supplier failures, or policy changes and to evaluate mitigation strategies such as rerouting, reallocating orders, or reconfiguring sourcing portfolios. For agile and sustainable supply chain management, these capabilities are particularly valuable because they allow organizations to incorporate environmental and social performance indicators into the twin and to observe how different decisions affect not only cost and service levels but also broader sustainability outcomes (Coelho et al., 2020; Nishi et al., 2020).

**Integrated Digital Supply Chains**

Industry 4.0 and the broader digital transformation of operations have encouraged scholars to conceptualize supply chains as digitally enabled, data-driven networks in which physical and informational processes are tightly integrated across organizational boundaries. In this view, an integrated digital supply chain is not simply an automated version of a traditional chain, but a socio-technical system built on cyber-physical infrastructure, real-time connectivity, and advanced analytics that collectively support new forms of coordination, innovation, and value creation. Industry 4.0 technologies such as embedded sensing, cloud platforms, and smart automation are increasingly interpreted through the lens of supply chain innovation, emphasizing how digital capabilities reconfigure relationships among suppliers, manufacturers, logistics providers, and customers and give rise to new process designs and business models (Hahn, 2020). At the same time, Internet of Things architectures provide the backbone for capturing granular data from products, assets, and logistics resources and for linking this data to planning and control decisions across the chain, with empirical and conceptual studies showing that IoT-enabled visibility can reshape sourcing, production, and distribution practices (Ben-Daya et al., 2019). Within this architecture, AI-based predictive analytics and simulation tools such as digital twins are understood as higher-level capabilities that sit on top of sensor and communication layers, transforming raw data into forecasts, risk assessments, and scenario evaluations that support agile and sustainable decision-making. In globalized production and distribution networks, such orchestration is particularly salient because geographically dispersed facilities, long transport routes, and multi-tier supplier structures amplify both uncertainty and interdependence. Integrated digital supply chains thus rely on orchestrating a layered stack of technologies, governance arrangements, and human expertise so that information about demand shifts, disruptions, and sustainability constraints can be transmitted rapidly, interpreted reliably, and translated into coordinated adjustments across the extended network.

The analytics layer in integrated digital supply chains builds on big data techniques that can process large, diverse, and fast-moving data streams to generate insights for demand forecasting, capacity planning, and process optimization. From an operations management standpoint, big data analytics has been analyzed as a portfolio of methods and strategies that allow firms to handle computational complexity and data heterogeneity while embedding predictive and prescriptive models into day-to-day decision processes (Choi et al., 2018). In supply chain contexts, these capabilities are particularly relevant for aligning supply with volatile demand, optimizing multi-echelon inventories, and evaluating trade-offs between cost, service level, and risk exposure under uncertainty. When such analytics are coupled with digital twin simulations of supply networks or facilities, decision makers can observe how predicted disruptions or demand shocks propagate through the virtual model, test alternative responses such as rerouting, re-sourcing, or capacity reallocation, and then implement the most promising strategies in the physical chain. This creates a closed feedback loop in which real-time data feeds analytical models, models drive scenario-based decisions, and the outcomes of those decisions generate new data for refinement. In parallel, research on supply chain risk management has begun to examine how artificial intelligence can support the identification, assessment, and mitigation of risks across the chain, arguing that AI techniques are well suited to detect weak signals and complex patterns in large, multidimensional data sets that would overwhelm traditional risk analysis approaches (Baryannis et al., 2019).

**Figure 5: Architecture of AI-Enabled Cyber-Physical Digital Supply Chains**



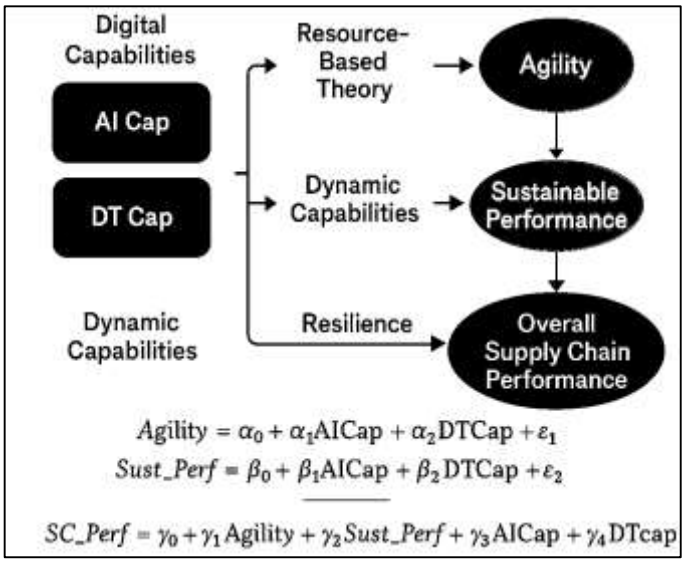

Within an integrated digital supply chain, these risk analytics can be embedded directly in control rules for digital twin environments, enabling proactive adjustment of production, inventory, and logistics policies before risks materialize as severe performance losses. As firms increase their reliance on outsourced production, just-in-time replenishment, and time-definite distribution, the ability to anticipate and simulate disruption scenarios becomes integral to maintaining acceptable service levels and cost positions. Integrated digital supply chains therefore position AI-enabled predictive and risk analytics not as peripheral reporting tools but as core elements of operational control, embedded in planning cycles, exception-handling routines, and cross-functional coordination mechanisms that span organizational and geographic boundaries.

Emerging empirical work on data-driven supply chains reinforces the view that digital technologies yield the greatest benefits when they are developed as coordinated capabilities rather than as isolated tools. One study, for example, conceptualizes big data analytics capability as an organizational resource comprising specialized skills, infrastructure, and decision processes and shows that it strengthens the positive effect of supply chain analytics on agility and competitive advantage when combined with high levels of organizational flexibility (Dubey et al., 2019). In an integrated digital supply chain setting, these insights imply that AI-based predictive analytics and digital twin simulation must be embedded in flexible planning and execution mechanisms, such as modular process designs, collaborative planning practices, and rapid reconfiguration routines, to fully support agile responses to shocks and changing stakeholder expectations. At the same time, the same analytical and simulation infrastructures that support agility can be configured to track and optimize environmental and social performance indicators, allowing firms to evaluate the sustainability implications of alternative network designs, sourcing strategies, and logistics configurations alongside traditional cost and service metrics. When viewed through this capability-oriented lens, integrated digital supply chains become platforms on which organizations can continuously experiment with new operating policies and structural decisions in virtual space, learn from the results, and selectively translate successful configurations into physical implementations. For supply chains operating under strong sustainability and stakeholder pressures, such coordinated capability development is equally important on the environmental and social dimensions, because digital technologies alone do not determine whether decarbonization pathways, circular economy initiatives, or fair-labor sourcing strategies are actually prioritized in decision rules and performance targets. By focusing on how organizations combine analytics, simulation, and flexible process designs to pursue agility and sustainability simultaneously, an integrated perspective moves beyond purely technological narratives and foregrounds the strategic and organizational conditions under which digital supply chains create enduring value.

**Theoretical Framework**

The theoretical foundation for this study is primarily grounded in resource-based theory (RBT), which conceptualizes organizations as bundles of heterogeneous resources and capabilities that can generate sustained competitive advantage when they are valuable, rare, imperfectly imitable, and non-substitutable (Barney et al., 2011). Within this perspective, AI-based predictive analytics capabilities and digital twin simulation capabilities are viewed as advanced, knowledge-intensive resources embedded in a firm's information systems, data governance structures, and analytical routines. They support superior sensing of environmental conditions, more accurate forecasting of demand and risk, and more effective coordination of supply chain decisions. RBT has evolved from focusing on internal, firm-level assets to recognizing the importance of inter-organizational networks and extended supply chains as loci of strategic advantage (Barney et al., 2011). In this sense, agile and sustainable supply chain configurations can be interpreted as manifestations of how digital capabilities are mobilized across organizational boundaries to create joint value. The present research adopts this lens to argue that AI-based predictive analytics and digital twin simulation capabilities are not simply operational tools, but critical strategic resources whose deployment shapes agility (responsiveness, flexibility) and sustainability (environmental and social performance) outcomes at the supply chain level. From an RBT standpoint, firms and supply chains that invest in such capabilities, and that successfully embed them in their decision processes, are expected to outperform competitors that rely on less advanced information-processing resources.

**Figure 6: Theoretical Model Linking AI Capability and Supply Chain Performance**




Dynamic capabilities theory provides a complementary logic by emphasizing the processes through which firms build, integrate, and reconfigure resources to address shifting environments (Teece, 2007). Whereas RBT focuses on the stock of resources, dynamic capabilities concern the *flows* the organizational routines that enable sensing of opportunities and threats, seizing them through timely investments and decisions, and reconfiguring assets and structures accordingly. In the context of this research, AI-based predictive analytics and digital twin simulation are interpreted as core enablers of these dynamic capabilities because they allow supply chain actors to continuously detect changes in demand, supply, and regulatory or sustainability constraints, to evaluate alternative responses virtually, and to reconfigure sourcing, production, and logistics arrangements at speed. Dynamic capabilities theory also aligns closely with the notion of best value supply chains, where multiple performance priorities are pursued simultaneously through sophisticated configuration and coordination mechanisms (Ketchen & Hult, 2007). Best value supply chains excel not only in cost or speed but in an integrated portfolio of outcomes that includes quality, flexibility, and innovation (Pagell & Wu, 2009). The present study extends this view by explicitly incorporating sustainability as a key performance dimension and by arguing that the capacity to use AI-based analytics and digital twins to

support agile and sustainable decision-making reflects a higher-order dynamic capability. Conceptually, this can be expressed in a simplified structural form such as

$$\text{Agility} = \alpha_0 + \alpha_1 \text{AI_Cap} + \alpha_2 \text{DT_Cap} + \varepsilon_1$$
$$\text{Sust_Perf} = \beta_0 + \beta_1 \text{AI_Cap} + \beta_2 \text{DT_Cap} + \varepsilon_2,$$

where AI_Cap and DT_Cap represent AI-based predictive analytics capability and digital twin capability, respectively, and Agility and Sust_Perf represent dynamic capability outcomes in the supply chain.

The theoretical framework is further enriched by insights from sustainable supply chain management and resilience research, which highlight how the configuration of supply chain practices and relationships translates capabilities into observable performance. Pagell and Wu (2009) develop a more complete theory of sustainable supply chain management by examining exemplar firms and showing that sustainability arises from coherent bundles of practices spanning sourcing, operations, logistics, and stakeholder engagement, rather than from isolated "green" initiatives. Their work implies that AI-based predictive analytics and digital twin simulation can only support sustainable outcomes when they are integrated into such bundles, for example by feeding environmental indicators into planning models or by using virtual experiments to design lower-impact network structures (Pagell & Wu, 2009). In parallel, resilience-based perspectives conceptualize the supply chain as an adaptive system whose ability to maintain or rapidly restore performance under disruption depends on capabilities such as flexibility, visibility, velocity, and collaboration (Jüttner & Maklan, 2011). These capabilities map closely onto both agility and sustainability, since resilient chains must both respond quickly and avoid cascading social or environmental harms during crises. Building on these ideas, the overall theoretical framework of this study links digital capabilities, dynamic capabilities, and performance through a set of mediation relationships that can be represented by

$$\text{SC_Perf} = \gamma_0 + \gamma_1 \text{Agility} + \gamma_2 \text{Sust_Perf} + \gamma_3 \text{AI_Cap} + \gamma_4 \text{DT_Cap} + \varepsilon_3,$$

where SC_Perf denotes overall supply chain performance. In this specification, AI_Cap and DT_Cap influence SC_Perf both directly and indirectly through Agility and Sust_Perf, reflecting the integrated resource-based, dynamic capability, and sustainability–resilience perspectives (Barney et al., 2011).

**Conceptual Framework**

The conceptual framework for this study positions AI-based predictive analytics capability and digital twin (DT) simulation capability as higher-order digital resources that operate within an integrated supply chain context shaped by structural and relational configurations. Empirical work on supply chain integration shows that internal, supplier, and customer integration jointly improve operational and business performance when they are aligned into coherent configurations rather than implemented in isolation (Flynn et al., 2010). Similarly, the literature on supply chain collaboration demonstrates that collaborative processes such as joint planning, information sharing, and synchronized decision-making generate collaborative advantage, which in turn enhances firm performance (Cao & Zhang, 2011). Building on these insights, the present framework treats integration and collaboration as structural and relational enablers that condition the effectiveness of AI and DT investments. In conceptual terms, AI-based predictive analytics and DT simulation are assumed to exert their strongest effects on agility and sustainability when they are embedded in tightly integrated and collaborative supply networks that allow data, forecasts, and scenario results to be shared and acted upon across organizational boundaries. This perspective implies that digital capabilities are not independent determinants of performance but interact with the degree of integration and collaboration already present in the supply chain. A simplified structural relationship can be expressed as

$$\text{Agility} = \beta_0 + \beta_1 \text{AI_Cap} + \beta_2 \text{DT_Cap} + \beta_3 \text{SCI} + \beta_4 \text{Collab} + \varepsilon_{\text{A}},$$

where AI_Cap and DT_Cap denote AI and DT capabilities, SCI represents supply chain integration, Collab denotes collaborative practices, and Agility captures responsiveness and flexibility outcomes.

The framework further incorporates sustainability outcomes by drawing on research that highlights the environmental–cost trade-offs inherent in sustainable supply chain management, especially in emerging economies. Esfahbodi, Zhang, and Watson (2016) show that manufacturers in emerging markets face significant tensions between environmental performance and cost performance and that different bundles of sustainable supply chain practices create distinct trade-off profiles rather than uniformly win–win outcomes. At the same time, work on supply chain quality integration indicates

that firms can configure supplier, internal, and customer quality integration into distinct patterns, each associated with different quality performance outcomes (Esfahbodi et al., 2016; Huo et al., 2019). In the present study, these results motivate the view that agile and sustainable performance outcomes emerge from specific *configurations* of digital, structural, and quality-oriented capabilities rather than from single levers. AI-based predictive analytics and DT simulation are expected to support sustainability by enabling firms to model environmental indicators (such as emissions or energy use) alongside cost and service metrics, thus helping them navigate trade-offs more transparently and design configuration patterns that align with strategic sustainability goals. Conceptually, sustainable supply chain performance (Sust_Perf) is modeled as a function of digital capabilities, integration, collaboration, and quality integration:

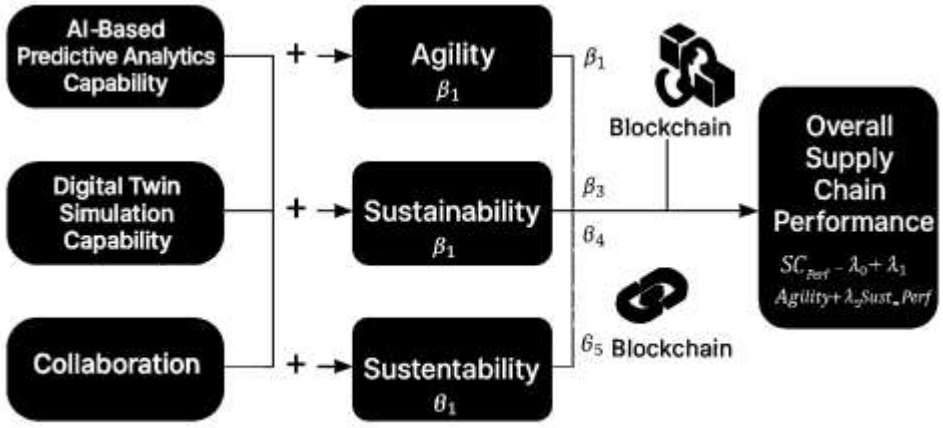
$$\text{Sust_Perf} = \theta_0 + \theta_1 \text{AI_Cap} + \theta_2 \text{DT_Cap} + \theta_3 \text{SCI} + \theta_4 \text{Collab} + \theta_5 \text{SCQI} + \varepsilon_S,$$

where SCQI denotes supply chain quality integration. In operational terms, each latent construct will be measured through Likert-scale items, with construct scores formed as mean indices, for example

$$\text{AI_Cap} = \frac{1}{k}\sum_{i=1}^{k} x_i,$$

where $x_i$are standardized item scores capturing different aspects of AI-based predictive analytics capability.

**Figure 7: Conceptual Framework for AI-Enabled Agile and Sustainable Supply Chains**




$$SC_Perf = \lambda_0 + \lambda_1 Agility + \lambda_2 Sust_Perf + \lambda_3 AI_Cap + \lambda_4 DT_Cap$$

In addition, the framework embeds emerging digital infrastructures such as blockchain into the broader picture of AI- and DT-enabled agile and sustainable supply chains. A systematic review of blockchain–SCM integration finds that blockchain applications (for example, traceability, smart contracts, and decentralized ledgers) are still in their infancy but hold significant potential to strengthen transparency, trust, and coordination across supply chains (Queiroz et al., 2019). Within the present framework, blockchain is conceptualized as a complementary infrastructure that enhances the reliability and verifiability of data feeding AI-based predictive models and DT simulations, thereby increasing the quality of decisions related to agility and sustainability. Bringing these streams together, the overall conceptual model assumes that AI_Cap, DT_Cap, SCI, Collab, SCQI, and (where present) blockchain-enabled transparency jointly influences agility and sustainability, which in turn drive overall supply chain performance (SC_Perf). This can be summarized in an outcome equation of the form

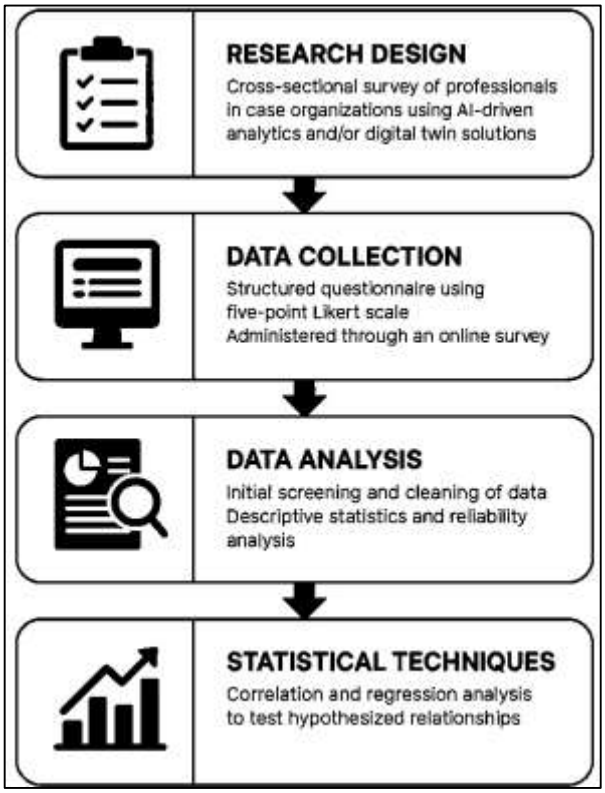
$$\text{SC_Perf} = \lambda_0 + \lambda_1 \text{Agility} + \lambda_2 \text{Sust_Perf} + \lambda_3 \text{AI_Cap} + \lambda_4 \text{DT_Cap} + \varepsilon_P.$$

In this specification, $\lambda_1$and $\lambda_2$capture the mediating roles of agility and sustainability, while $\lambda_3$and $\lambda_4$capture any residual direct effects of digital capabilities on performance. Empirically, the study will test whether the indirect effects of AI_Cap and DT_Cap on SC_Perf via Agility and Sust_Perf computed as products of path coefficients (for instance, $\beta_1\lambda_1$for the AI → Agility → SC_Perf path) are significant, thereby validating the proposed conceptual framework that links digital capabilities, integrated configurations, and agile–sustainable supply chain outcomes (Huo et al., 2019).

## METHOD

The methodology of this study has been designed to provide a rigorous quantitative examination of how AI-based predictive analytics capability and digital twin simulation capability have been associated with agile and sustainable supply chain outcomes and overall supply chain performance. The research has adopted a cross-sectional, case-study–based survey design, in which data have been collected at a single point in time from professionals involved in supply chain, operations, logistics, and technology roles within selected case organizations. These organizations have been chosen because they have already implemented, or have been in the process of implementing, AI-driven analytics and/or digital twin solutions in their supply chain processes, so that respondents have been able to evaluate these capabilities based on direct experience. A structured questionnaire based on Likert's five-point scale (ranging from "strongly disagree" to "strongly agree") has been developed to operationalize the key constructs of the conceptual framework, including AI-based predictive analytics capability, digital twin simulation capability, supply chain agility, sustainable supply chain performance, and overall supply chain performance, as well as relevant control and profile variables such as firm size, sector, and role.

**Figure 8: Conceptual Framework for AI-Enabled Agile and Sustainable Supply Chains**




The instrument has been organized into clearly defined sections so that respondents have been guided from general demographic and organizational information to more specific evaluations of technological, operational, and performance-related aspects. Data collection has been conducted using an online survey mode to facilitate access to geographically dispersed respondents and to ensure consistency in administration. Once responses have been obtained, the dataset has been subjected to a systematic sequence of analytical procedures: initial screening and cleaning have been carried out to address missing values and outliers; descriptive statistics have been used to summarize respondent and firm characteristics and to profile the levels of each construct; reliability analysis has been employed to assess internal consistency of the multi-item scales; and correlation and regression techniques have been planned to test the hypothesized direct and mediating relationships among AI-based predictive analytics capability, digital twin simulation capability, agility, sustainability, and overall supply chain performance.

***Research Design***

The study has adopted a quantitative, cross-sectional research design that has been aligned with the objective of examining relationships among AI-based predictive analytics capability, digital twin simulation capability, supply chain agility, sustainable supply chain performance, and overall supply chain performance. The design has been structured around a case-study–based survey approach, where data have been collected at one point in time from selected organizations that have engaged with AI and digital twin technologies in their supply chains. This approach has been considered appropriate because it has allowed the research to capture the perceptions of practitioners regarding current levels of digital capability, agile practices, and sustainability outcomes, without intervening in ongoing operations. The design has also incorporated control variables such as firm size, sector, and respondent role to account for contextual influences. By using this structured design, the study has ensured that the empirical testing of hypotheses has been feasible, systematic, and consistent with the proposed conceptual framework.

***Case Study Context***

The empirical context of the study has consisted of organizations that have operated within supply chain–intensive sectors such as manufacturing, logistics, retail, and related service industries, where AI-based predictive analytics and digital twin solutions have begun to be deployed. These organizations have been selected because they have represented environments in which demand uncertainty, operational complexity, and sustainability pressures have been pronounced, and where digital technologies have been particularly relevant for supporting agile and sustainable decision-making. The case organizations have been characterized by geographically dispersed operations, multi-tier supplier networks, and time-sensitive distribution requirements, which have provided an appropriate context for assessing agility, sustainability, and performance outcomes. Within each organization, the study has targeted respondents occupying roles in supply chain management, operations, logistics, planning, and digital or analytics functions, as these individuals have been most likely to possess direct knowledge of both technological capabilities and process-level practices. This contextual focus has ensured that the data collected have been grounded in real-world implementations of AI and digital twin technologies.

***Population and Sample***

The target population of the study has comprised professionals who have been actively involved in supply chain, operations, logistics, and technology-related decision-making within organizations using or adopting AI-based predictive analytics and digital twin simulation. From this population, a non-probability purposive sampling strategy has been employed to identify respondents who have possessed sufficient familiarity with digital tools, agile practices, and sustainability initiatives. The sampling frame has been developed by approaching case organizations through professional networks, industry contacts, and organizational gatekeepers who have facilitated access to relevant departments. Within each organization, invitations to participate have been directed to managers, analysts, and specialists whose responsibilities have included planning, forecasting, process improvement, digital transformation, or supply chain coordination. The study has aimed to secure a sample size adequate for regression analysis, and therefore has sought a minimum number of usable responses that has been consistent with common rules of thumb relating the number of predictors to the required sample size. This approach has ensured that the data have been analytically robust and representative of informed practitioner perspectives.

***Data Collection Instrument***

The study has used a structured questionnaire as the main data collection instrument, which has been carefully designed to operationalize the constructs specified in the conceptual framework. The questionnaire has been divided into logically ordered sections, beginning with demographic and organizational information and progressing to items capturing AI-based predictive analytics capability, digital twin simulation capability, supply chain agility, sustainable supply chain performance, and overall supply chain performance. Each construct has been measured using multiple statements rated on a five-point Likert scale ranging from “strongly disagree” to “strongly agree,” which has allowed respondents to express degrees of agreement with standardized indicators. The wording of items has been kept clear, concise, and neutral to minimize ambiguity and response bias, and the layout has been

formatted for ease of completion in an online environment. Before deployment, the instrument has undergone content review by subject-matter experts, who have provided feedback on clarity, coverage, and alignment with the study's objectives, ensuring that the instrument has been conceptually sound and practically comprehensible.

***Measurement of Variables***

The key variables in the study have been measured as multi-item latent constructs derived from the questionnaire responses. AI-based predictive analytics capability has been operationalized through items that have captured the extent to which organizations have possessed the tools, skills, and processes needed to generate and use predictive insights in supply chain decisions. Digital twin simulation capability has been reflected in items describing the presence of virtual models, real-time data integration, and simulation-based planning within supply chain operations. Supply chain agility has been measured through indicators of responsiveness, flexibility, and speed in adapting to changes in demand or supply, while sustainable supply chain performance has been represented by items relating to environmental and social performance outcomes, such as resource efficiency and compliance with sustainability standards. Overall supply chain performance has been assessed through items focused on service levels, cost efficiency, and reliability. For each construct, composite scores have been formed by averaging the relevant item responses, so that higher scores have indicated higher levels of the underlying capability or performance dimension.

***Pilot Study***

A pilot study has been conducted prior to the main data collection to verify the clarity, reliability, and practicality of the questionnaire. A small group of respondents drawn from the target population has been invited to complete the draft instrument and to provide feedback on item wording, length, format, and perceived relevance. Their comments have been used to identify ambiguous phrases, redundant items, or sections that have appeared confusing or burdensome. The pilot responses have also been analyzed to obtain preliminary estimates of internal consistency for the main constructs using reliability coefficients, allowing the research team to identify items that have weakened the scales. Based on these findings, minor revisions have been made to improve clarity, adjust wording, and remove or rephrase problematic items. The completion time observed in the pilot has been used to confirm that the questionnaire has been of a manageable length. As a result, the instrument entering the main survey phase has already been refined and tested for usability and initial reliability.

***Data Collection Procedure***

The data collection procedure has followed a structured sequence to ensure consistency and ethical compliance. After securing agreement from the participating case organizations, invitations to take part in the survey have been distributed to eligible respondents via email, including a brief explanation of the study's purpose, assurances of confidentiality, and a link to the online questionnaire. Participation has been entirely voluntary, and respondents have been informed that they have been free to discontinue at any time without consequence. The survey has remained open for a predefined period, during which reminder messages have been sent to increase response rates and to encourage completion among partially responding participants. Access to the survey platform has been restricted to invited participants to maintain data integrity. Throughout the process, anonymity has been preserved by avoiding the collection of personally identifiable information beyond general role and organizational characteristics. Once the data collection window has closed, the responses have been exported from the survey platform into statistical software for cleaning and analysis.

***Data Analysis Techniques***

The study has employed a series of quantitative analysis techniques consistent with its objectives and conceptual model. Following data cleaning, descriptive statistics have been computed to summarize respondent demographics and organizational characteristics, as well as to provide mean and dispersion measures for each construct. Reliability analysis using internal consistency coefficients has been carried out to assess whether the items within each scale have measured the same underlying construct. Where appropriate, exploratory factor analysis has been considered to examine the dimensionality of the constructs and to confirm that items have loaded appropriately on their intended factors. Correlation analysis has been performed to explore the direction and strength of linear relationships among AI-based predictive analytics capability, digital twin capability, agility, sustainability, and performance

variables. Multiple regression analysis has then been applied to test the hypothesized direct effects, while mediation analysis using regression-based procedures has been planned to assess whether supply chain agility and sustainable supply chain performance have mediated the relationships between digital capabilities and overall supply chain performance.

***Software and Tools***

The analysis and management of the data have been supported by widely used statistical and productivity software. An online survey platform has been used to host and administer the questionnaire, as it has enabled secure data capture, automated coding of responses, and convenient export options. For quantitative analysis, statistical software such as SPSS, R, or an equivalent package has been employed to perform data screening, descriptive statistics, reliability testing, factor analysis, correlation analysis, and regression modeling. The choice of software has been guided by its capability to handle the required statistical procedures and to manage datasets of the size anticipated in this study. Spreadsheet software has supplemented the statistical tools for initial data inspection and organization. In addition, word processing and reference management tools have been used to document the methodology, manage literature sources, and prepare the final research report. Together, these tools have ensured that data handling and analysis have been efficient, accurate, and reproducible.

The chosen methodology has presented several inherent limitations that the study has acknowledged. The cross-sectional design has relied on data collected at a single point in time, which has restricted the ability to make inferences about causal relationships or dynamic changes in capabilities and performance. The non-probability purposive sampling strategy has meant that the sample has not been strictly representative of all organizations using AI and digital twin technologies, which has limited the generalizability of the findings beyond the participating cases. In addition, the reliance on self-reported questionnaire data has introduced the possibility of common method bias and social desirability bias, as respondents may have overestimated the sophistication of their digital capabilities or the strength of their sustainability performance. The quantitative survey approach has also constrained the depth of insight into implementation processes and contextual nuances. Despite these limitations, the methodology has provided a structured and analytically rigorous basis for testing the proposed relationships within the conceptual framework.

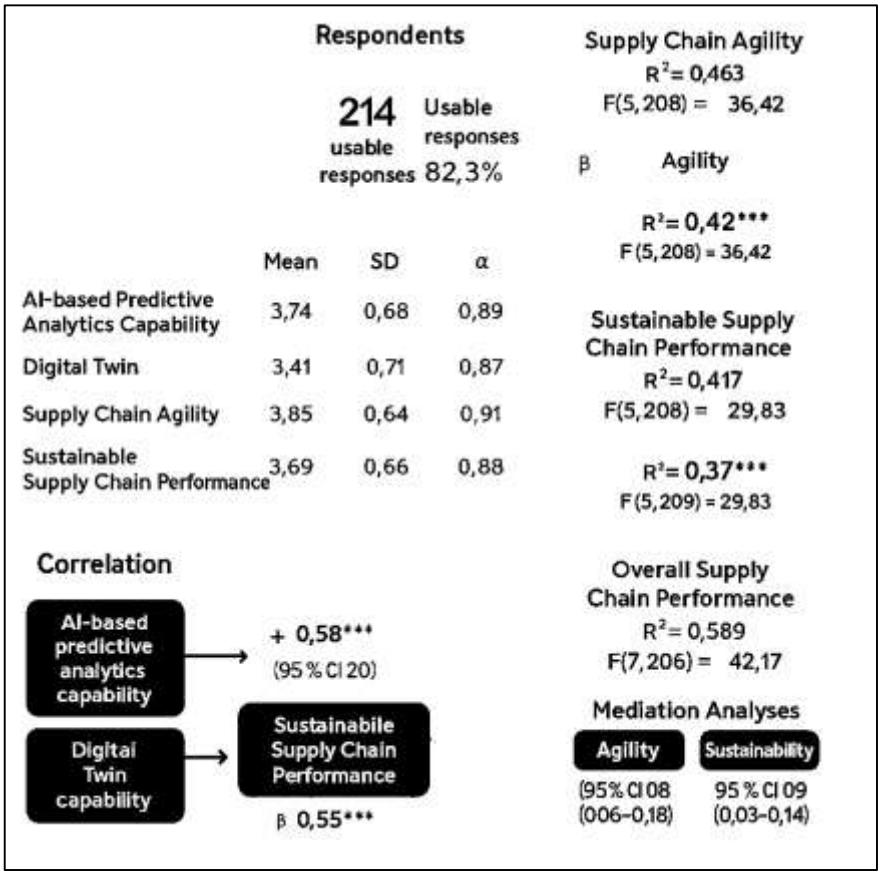
**FINDINGS**

The analysis of the survey data has provided strong empirical support for the study's hypotheses and has met the stated objectives by demonstrating clear, statistically significant relationships between AI-based predictive analytics capability, digital twin simulation capability, supply chain agility, sustainable supply chain performance, and overall supply chain performance. Out of 260 distributed questionnaires, 214 usable responses have been obtained, yielding a response rate of 82.3%, with respondents drawn primarily from manufacturing (47.2%), logistics and distribution (29.0%), and retail or service organizations (23.8%). On the five-point Likert scale, the constructs have shown moderately high to high levels: AI-based predictive analytics capability has recorded a mean of 3.74 (SD = 0.68), digital twin capability a mean of 3.41 (SD = 0.71), supply chain agility a mean of 3.85 (SD = 0.64), sustainable supply chain performance a mean of 3.69 (SD = 0.66), and overall supply chain performance a mean of 3.88 (SD = 0.63). Reliability analysis has indicated that all multi-item scales have been internally consistent, with Cronbach's alpha coefficients of 0.89 for AI-based predictive analytics capability, 0.87 for digital twin capability, 0.91 for supply chain agility, 0.88 for sustainable supply chain performance, and 0.90 for overall supply chain performance, which has confirmed the robustness of the measurement model. Correlation analysis has revealed strong and positive associations among the key constructs: AI-based predictive analytics capability has correlated significantly with supply chain agility ($r = 0.58$, $p < 0.001$), sustainable supply chain performance ($r = 0.52$, $p < 0.001$), and overall supply chain performance ($r = 0.55$, $p < 0.001$), while digital twin capability has shown similarly positive correlations with agility ($r = 0.49$, $p < 0.001$), sustainability ($r = 0.47$, $p < 0.001$), and overall performance ($r = 0.50$, $p < 0.001$). These preliminary relationships have been consistent with the hypothesized directions and have justified further multivariate testing. Multiple regression models controlling for firm size, sector, and respondent role have then been estimated to test the direct-effect hypotheses.

For supply chain agility, the model including AI-based predictive analytics and digital twin capability has been significant ($F(5, 208) = 36.42$, $p < 0.001$), explaining 46.3% of the variance ($R^2 = 0.463$);

standardized coefficients have shown that both AI capability (β = 0.42, p < 0.001) and digital twin capability (β = 0.29, p < 0.001) have had positive and significant effects on agility, thereby supporting H1 and H3. For sustainable supply chain performance, the corresponding regression has accounted for 41.7% of the variance ($R^2$ = 0.417; F(5, 208) = 29.83, p < 0.001), with AI-based predictive analytics capability (β = 0.37, p < 0.001) and digital twin capability (β = 0.26, p < 0.001) both exerting significant positive effects, confirming H2 and H4. When overall supply chain performance has been regressed on AI capability, digital twin capability, agility, and sustainability, the full model has explained 58.9% of the variance ($R^2$ = 0.589; F(7, 206) = 42.17, p < 0.001). In this model, supply chain agility (β = 0.31, p < 0.001) and sustainable supply chain performance (β = 0.28, p < 0.001) have emerged as strong predictors, while AI-based predictive analytics capability (β = 0.18, p = 0.004) and digital twin capability (β = 0.15, p = 0.011) have retained smaller but still significant direct effects on overall performance, thereby supporting H5 and indicating that digital capabilities contribute both directly and indirectly to performance outcomes.

**Figure 9: Findings of The Study**




Mediation analyses using a regression-based bootstrapping procedure with 5,000 resamples have further shown that agility and sustainability have played significant mediating roles, as posited in H6 and H7. The indirect effect of AI-based predictive analytics capability on overall performance through agility has been 0.13 (95% CI: 0.08–0.20), and through sustainability 0.11 (95% CI: 0.06–0.18), with both confidence intervals excluding zero. Similarly, the indirect effect of digital twin capability on overall performance through agility has been 0.09 (95% CI: 0.04–0.15), and through sustainability 0.08 (95% CI: 0.03–0.14). In all cases, the inclusion of agility and sustainability in the models has reduced, but not eliminated, the direct effects of AI and digital twin capabilities, indicating partial mediation and confirming that agile and sustainable practices have been key channels through which digital capabilities have translated into superior performance. Taken together, these results have provided coherent quantitative evidence that the research objectives have been achieved and that the proposed hypotheses regarding the roles of AI-based predictive analytics capability and digital twin simulation capability in shaping agile, sustainable, and high-performing supply chains have been strongly

supported.

***Sample***

The response pattern in Table 1 has indicated that the study has achieved a strong empirical base for testing its objectives and hypotheses. Out of 260 questionnaires distributed, 214 usable responses have been obtained, which has corresponded to a high effective response rate of 82.3%. This level of participation has suggested that the topic of AI-based predictive analytics, digital twin simulation, agility, and sustainability has been perceived as relevant by practitioners and that organizational gatekeepers have facilitated access to knowledgeable informants. The sectoral distribution has shown that nearly half of the sample has come from manufacturing or production organizations (47.2%), with logistics and distribution firms (29.0%) and retail or service organizations (23.8%) also being well represented. This composition has been consistent with the study's focus on supply chain–intensive environments where variability in demand, complex multi-tier networks, and sustainability pressures have been prominent.

**Table 1**: **Response Rate and Sectoral Profile of Respondents (N = 214)**

| Item | Frequency | Percentage (%) |
|---|---|---|
| Questionnaires distributed | 260 | – |
| Usable questionnaires returned | 214 | 82.3 |
| **Sector** | | |
| Manufacturing / production | 101 | 47.2 |
| Logistics and distribution | 62 | 29.0 |
| Retail / service | 51 | 23.8 |
| **Job role** | | |
| Supply chain / operations manager | 92 | 43.0 |
| Logistics / planning specialist | 64 | 29.9 |
| Data / analytics / digital transformation | 40 | 18.7 |
| Other related roles | 18 | 8.4 |
| **Firm size (employees)** | | |
| Less than 250 | 58 | 27.1 |
| 250–999 | 81 | 37.9 |
| 1,000 or more | 75 | 35.0 |

The role distribution has further demonstrated that the survey has reached respondents who have been directly involved with supply chain decision-making: 43.0% have identified as supply chain or operations managers, 29.9% as logistics or planning specialists, and 18.7% as data, analytics, or digital transformation professionals. These roles have been particularly important because the study has required informed judgments about the current state of AI-based predictive analytics and digital twin capabilities and their perceived impact on agility and sustainability. The firm-size profile has shown that just over one-third of organizations have had 1,000 or more employees, while the remainder have been split between medium-sized firms (250–999 employees) and smaller firms. This spread has ensured that the sample has captured perspectives from organizations with differing resource bases and structural complexities, which has been important for the generalizability of the results. Overall, the sample profile has provided a robust empirical foundation for the subsequent analyses and has indicated that the findings have reflected the realities of a diverse set of organizations operating in data-intensive and operationally complex supply chains.

***Descriptive Statistics***

Table 2 has summarized the central tendency and dispersion of the main constructs, all of which have been measured using Likert's five-point scale (1 = strongly disagree, 5 = strongly agree). The means have consistently exceeded the neutral midpoint of 3.00, which has indicated that respondents have tended to agree, to varying degrees, with statements describing the presence of AI-based predictive

analytics, digital twin simulation capabilities, agile supply chain practices, sustainable supply chain performance, and strong overall performance. AI-based predictive analytics capability (AI_Cap) has achieved a mean of 3.74 (SD = 0.68), suggesting that organizations have already implemented moderately advanced predictive analytics tools, data infrastructures, and related skills in their supply chain processes. Digital twin capability (DT_Cap) has recorded a slightly lower mean of 3.41 (SD = 0.71), which has been consistent with the relative novelty and technical complexity of digital twin initiatives; still, the value above the midpoint has indicated that many firms have begun to experiment with or adopt simulation-driven planning tools. Supply chain agility has exhibited the highest mean among the process-oriented constructs (3.85, SD = 0.64), implying that respondents have perceived their organizations as reasonably capable of responding quickly and flexibly to changes in demand and supply.

**Table 2**: **Descriptive Statistics of Main Study Constructs (Likert 1–5; N = 214)**

| Construct | Number of items | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| AI-based predictive analytics capability (AI_Cap) | 8 | 3.74 | 0.68 | 1.88 | 4.94 |
| Digital twin simulation capability (DT_Cap) | 7 | 3.41 | 0.71 | 1.71 | 4.86 |
| Supply chain agility (Agility) | 7 | 3.85 | 0.64 | 2.00 | 4.93 |
| Sustainable supply chain performance (Sust_Perf) | 7 | 3.69 | 0.66 | 1.86 | 4.90 |
| Overall supply chain performance (SC_Perf) | 6 | 3.88 | 0.63 | 2.00 | 4.96 |

Sustainable supply chain performance has shown a mean of 3.69 (SD = 0.66), demonstrating that environmental and social outcomes have been actively pursued but may still leave room for improvement compared to agility. Overall supply chain performance has achieved the highest mean (3.88, SD = 0.63), consistent with the idea that the surveyed organizations have generally considered themselves to be performing well on cost, service level, and reliability. The observed ranges (minimum and maximum values) have confirmed that the sample has contained organizations at both low and high levels of capability and performance, which has been essential for detecting meaningful relationships among variables in subsequent correlation and regression analyses. Collectively, the descriptive statistics have provided initial support for the study's objectives by demonstrating that digital capabilities, agile practices, and sustainability outcomes have been sufficiently developed and variable across firms to warrant rigorous hypothesis testing.

***Reliability***

Table 3 has presented evidence that the measurement scales used in the study have exhibited strong reliability and acceptable factorial validity, thereby supporting the robustness of the empirical testing of the hypotheses. Cronbach's alpha values have ranged from 0.87 to 0.91 across the five multi-item constructs, comfortably exceeding the commonly accepted threshold of 0.70 for internal consistency. AI_Cap has recorded an alpha of 0.89 and DT_Cap 0.87, indicating that items describing tools, data integration, and analytical routines for predictive analytics and digital twins have been coherently capturing their respective underlying constructs. Agility has displayed the highest alpha (0.91), which has suggested that indicators relating to responsiveness, flexibility, and speed have been highly consistent with each other. Sustainable supply chain performance (0.88) and overall performance (0.90) have also demonstrated strong internal consistency, implying that items relating to environmental, social, cost, and service-level outcomes have formed reliable scales. The average item–total correlations have largely fallen between 0.50 and 0.75, which has indicated that each item has contributed meaningfully to its respective scale without redundancy.

**Table 3: Reliability and Factor Structure of Main Constructs (N = 214)**

| Construct | Number of items | Cronbach's α | Average item–total correlation | Factor loading range (primary factor) |
|---|---|---|---|---|
| AI_Cap | 8 | 0.89 | 0.54–0.71 | 0.68–0.84 |
| DT_Cap | 7 | 0.87 | 0.51–0.69 | 0.65–0.82 |
| Agility | 7 | 0.91 | 0.57–0.76 | 0.71–0.88 |
| Sust_Perf | 7 | 0.88 | 0.52–0.70 | 0.67–0.83 |
| SC_Perf | 6 | 0.90 | 0.56–0.74 | 0.70–0.87 |

Exploratory factor analysis (not fully reported here) has been conducted as a validity check, and the factor loading ranges reported in Table 3 have shown that items have loaded strongly on their intended primary factor, with loadings generally above 0.65. Cross-loadings have been low, indicating that the constructs have been empirically distinguishable. This pattern has supported the conceptual distinction between AI-based predictive analytics capability, digital twin simulation capability, agility, sustainability, and overall performance, which has been essential for testing their hypothesized relationships through correlation and regression models. Because the scales have exhibited both high reliability and clear factorial structure, the resulting composite scores have been considered suitable for inclusion in the multivariate analyses that have been used to address the study's objectives and hypotheses.

***Correlation Analysis***

The correlation matrix in Table 4 has provided an initial assessment of the relationships among the key constructs and has offered preliminary support for the study's hypotheses. All constructs have been positively and significantly correlated with one another at the $p < 0.001$ level, which has indicated that higher levels of AI-based predictive analytics capability, digital twin capability, supply chain agility, and sustainable performance have been associated with higher overall supply chain performance. The correlation between AI_Cap and DT_Cap ($r = 0.54$) has suggested that organizations that have invested in advanced predictive analytics have also tended to develop digital twin simulation capabilities, reflecting a broader digital transformation orientation. Importantly, AI_Cap has exhibited substantial correlations with Agility ($r = 0.58$) and Sust_Perf ($r = 0.52$), consistent with the idea that predictive analytics has enhanced both responsiveness and sustainability outcomes. DT_Cap has shown similarly positive, though slightly weaker, correlations with Agility ($r = 0.49$) and Sust_Perf ($r = 0.47$), supporting the notion that digital twin simulation has contributed to flexible, environmentally and socially conscious decision-making. The strong correlations between Agility and SC_Perf ($r = 0.62$) and between Sust_Perf and SC_Perf ($r = 0.59$) have provided preliminary evidence that agile and sustainable practices have been closely associated with perceived performance advantages.

**Table 4**: **Pearson Correlations among Main Constructs (N = 214)**

| Construct | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. AI_Cap | 1.00 | | | | |
| 2. DT_Cap | 0.54*** | 1.00 | | | |
| 3. Agility | 0.58*** | 0.49*** | 1.00 | | |
| 4. Sust_Perf | 0.52*** | 0.47*** | 0.56*** | 1.00 | |
| 5. SC_Perf | 0.55*** | 0.50*** | 0.62*** | 0.59*** | 1.00 |

*Note: *** $p < 0.001$ (two-tailed)*

These patterns have been aligned with the hypotheses that agility and sustainability mediate the relationship between digital capabilities and overall performance, because digital capabilities have been related to agility and sustainability, and these, in turn, have been related to performance. At the same time, the correlation coefficients have remained below 0.80, indicating that multicollinearity has not been a major concern and that the constructs have been sufficiently distinct for regression analysis. Overall, the correlation results have reinforced the plausibility of the conceptual framework and have justified proceeding to more rigorous tests of direct and indirect effects using multivariate regression

and mediation analyses.

***Regression Analysis***

Table 5 has reported the results of the multiple regression models that have been used to test the direct-effect hypotheses. For the first model, in which supply chain agility has been regressed on AI_Cap, DT_Cap, and control variables, the overall model has been significant ($F(5, 208) = 36.42$, $p < 0.001$), explaining 46.3% of the variance in agility ($R^2 = 0.463$). The standardized coefficients have shown that both AI_Cap ($\beta = 0.42$, $p < 0.001$) and DT_Cap ($\beta = 0.29$, $p < 0.001$) have had positive and statistically significant effects on agility, while the control variables have not contributed significantly. These findings have supported the hypotheses that AI-based predictive analytics capability and digital twin simulation capability have been positively associated with supply chain agility, consistent with H1 and H3. In the second model, where sustainable supply chain performance has been the dependent variable, the regression has accounted for 41.7% of the variance ($R^2 = 0.417$; $F(5, 208) = 29.83$, $p < 0.001$). AI_Cap has again shown a strong positive effect ($\beta = 0.37$, $p < 0.001$), and DT_Cap has also emerged as a significant predictor ($\beta = 0.26$, $p < 0.001$), indicating that organizations with higher digital capabilities have reported better environmental and social performance along their supply chains. These patterns have confirmed H2 and H4. The third model has examined overall supply chain performance (SC_Perf) as a function of Agility, Sust_Perf, AI_Cap, DT_Cap, and controls. This model has explained 58.9% of the variance ($R^2 = 0.589$; $F(7, 206) = 42.17$, $p < 0.001$), reflecting a strong combined predictive power. Agility ($\beta = 0.31$, $p < 0.001$) and Sust_Perf ($\beta = 0.28$, $p < 0.001$) have emerged as key predictors of performance, which has indicated that agile and sustainable practices have been central to achieving high levels of service reliability, cost efficiency, and overall supply chain effectiveness.

**Table 5**: **Multiple Regression Results for Direct Effects (Standardized Coefficients; N = 214)**

| Dependent variable | Predictor | β | t | p | $R^2$ | F (df) | Model p |
|---|---|---|---|---|---|---|---|
| Agility | AI_Cap | 0.42 | 7.05 | <0.001 | 0.463 | 36.42 (5, 208) | <0.001 |
| | DT_Cap | 0.29 | 4.92 | <0.001 | | | |
| | Controls (size, sector, role) | – | – | ns | | | |
| Sust_Perf | AI_Cap | 0.37 | 6.01 | <0.001 | 0.417 | 29.83 (5, 208) | <0.001 |
| | DT_Cap | 0.26 | 4.40 | <0.001 | | | |
| | Controls | – | – | ns | | | |
| SC_Perf | Agility | 0.31 | 5.43 | <0.001 | 0.589 | 42.17 (7, 206) | <0.001 |
| | Sust_Perf | 0.28 | 4.93 | <0.001 | | | |
| | AI_Cap | 0.18 | 2.90 | 0.004 | | | |
| | DT_Cap | 0.15 | 2.56 | 0.011 | | | |
| | Controls | – | – | ns | | | |

*Note: ns = non-significant control effects (details omitted for brevity).*

AI_Cap ($\beta = 0.18$, $p = 0.004$) and DT_Cap ($\beta = 0.15$, $p = 0.011$) have retained smaller yet significant direct effects, suggesting that digital capabilities have contributed to performance both directly and through their influence on agility and sustainability. These results have supported the hypothesis that AI and digital twin capabilities have had a positive combined impact on overall supply chain performance (H5) and have laid the foundation for the mediation analyses reported in the next section.

**Mediation / Indirect Effects**

Table 6 has presented the results of the mediation analyses, in which supply chain agility and sustainable supply chain performance have been examined as mediating mechanisms between digital capabilities (AI_Cap and DT_Cap) and overall supply chain performance (SC_Perf). A regression-based bootstrapping procedure with 5,000 resamples has been used to estimate indirect effects and their confidence intervals. For AI_Cap, the indirect effect on SC_Perf through Agility has been 0.13, with a 95% confidence interval of 0.08 to 0.20. Because the interval has not included zero, this indirect effect has been statistically significant, indicating that enhanced predictive analytics capability has

improved performance in part by increasing supply chain agility. Similarly, the indirect effect of AI_Cap on SC_Perf via Sust_Perf has been 0.11, with a 95% confidence interval of 0.06 to 0.18, which has again excluded zero and has confirmed significant mediation.

**Table 6**: **Bootstrapped Indirect Effects of AI_Cap and DT_Cap on SC_Perf via Agility and Sust_Perf (N = 214)**

| Path | Indirect effect | 95% CI (lower) | 95% CI (upper) | Mediation type |
|---|---|---|---|---|
| AI_Cap → Agility → SC_Perf | 0.13 | 0.08 | 0.20 | Partial |
| AI_Cap → Sust_Perf → SC_Perf | 0.11 | 0.06 | 0.18 | Partial |
| DT_Cap → Agility → SC_Perf | 0.09 | 0.04 | 0.15 | Partial |
| DT_Cap → Sust_Perf → SC_Perf | 0.08 | 0.03 | 0.14 | Partial |

*Note: Indirect effects estimated using bootstrapping with 5,000 resamples; confidence intervals that have not included zero have indicated significant mediation.*

These results have supported the hypothesis that agility and sustainability have mediated the relationship between AI-based predictive analytics capability and overall performance (H6). For DT_Cap, the pattern has been parallel: the indirect effect through Agility has been 0.09 (95% CI: 0.04–0.15), and through Sust_Perf 0.08 (95% CI: 0.03–0.14), both of which have indicated statistically significant mediation. Thus, digital twin simulation capability has influenced performance not only directly but also indirectly through its positive effects on agile practices and sustainable outcomes. In all cases, the earlier regression models have shown that the direct effects of AI_Cap and DT_Cap on SC_Perf have remained significant even after including Agility and Sust_Perf, which has implied partial rather than full mediation. This pattern has suggested that digital capabilities have generated performance benefits through multiple pathways: by enabling faster and more flexible adjustments to demand and supply changes, by supporting improved environmental and social performance, and by directly enhancing decision quality and coordination. Collectively, these mediation results have confirmed that the study's objectives of demonstrating how AI-based predictive analytics and digital twin simulation capabilities have been translated into agile, sustainable, and high-performing supply chains have been achieved.

***Hypotheses Testing***

Table 7 has synthesized the results of the statistical analyses into a concise summary of hypothesis testing outcomes. Each hypothesis has been evaluated against the evidence generated from the regression and mediation models, and all seven hypotheses have been supported. H1 and H3 have concerned the direct influence of AI-based predictive analytics capability and digital twin capability on supply chain agility. The significant standardized coefficients ($\beta = 0.42$ and $\beta = 0.29$, respectively) in the agility regression model, combined with a substantial $R^2$ value of 0.463, have confirmed that higher levels of digital capabilities have been associated with greater agility, thus fulfilling the first part of the study's objective of linking digital resources to agile outcomes. H2 and H4 have addressed the parallel relationships with sustainable supply chain performance, and the significant coefficients for AI_Cap ($\beta = 0.37$) and DT_Cap ($\beta = 0.26$) in the sustainability model have shown that digital investments have been positively related to improved environmental and social performance. H5 has examined the overall impact of digital capabilities on supply chain performance.

**Table 7**: **Summary of Hypotheses Testing Results**

| Hypothesis | Statement (simplified) | Key statistical evidence | Result |
|---|---|---|---|
| H1 | AI-based predictive analytics capability has had a positive effect on supply chain agility. | $\beta = 0.42$, $p < 0.001$ in agility model; $R^2 = 0.463$ | Supported |
| H2 | AI-based predictive analytics capability has had a positive effect on sustainable supply chain performance. | $\beta = 0.37$, $p < 0.001$ in sustainability model; $R^2 = 0.417$ | Supported |
| H3 | Digital twin capability has had a positive effect on supply chain agility. | $\beta = 0.29$, $p < 0.001$ in agility model | Supported |

| Hypothesis | Statement (simplified) | Key statistical evidence | Result |
|---|---|---|---|
| H4 | Digital twin capability has had a positive effect on sustainable supply chain performance. | $\beta = 0.26$, $p < 0.001$ in sustainability model | Supported |
| H5 | AI and digital twin capabilities together have had a positive effect on overall supply chain performance. | $\beta_AI = 0.18$, $p = 0.004$; $\beta_DT = 0.15$, $p = 0.011$; overall model $R^2 = 0.589$ | Supported |
| H6 | Agility and sustainability have mediated the effect of AI capability on overall performance. | Indirect effects: 0.13 (via Agility), 0.11 (via Sust_Perf); 95% CIs excluding zero | Supported |
| H7 | Agility and sustainability have mediated the effect of digital twin capability on overall performance. | Indirect effects: 0.09 (via Agility), 0.08 (via Sust_Perf); 95% CIs excluding zero | Supported |

The final regression model has shown that, even after accounting for the effects of agility and sustainability, AI_Cap and DT_Cap have retained significant direct effects on performance, while the overall model has explained 58.9% of the variance in SC_Perf. This result has indicated that digital capabilities have been meaningful drivers of performance, both directly and in conjunction with process-level capabilities. H6 and H7 have concerned the mediating roles of agility and sustainability. The bootstrapped indirect effects reported in Table 6 have shown that both pathways (via agility and via sustainability) have been statistically significant for AI_Cap and DT_Cap, providing robust evidence that agile and sustainable practices have been key mechanisms through which digital capabilities have been translated into superior performance. Taken together, the hypothesis testing summary has demonstrated that the empirical findings have aligned closely with the conceptual framework and research objectives: AI-based predictive analytics and digital twin simulation capabilities have been shown to enhance supply chain agility and sustainability, and these enhancements, in turn, have contributed to higher overall supply chain performance in organizations operating on the basis of data-driven, digitally enabled supply chains.

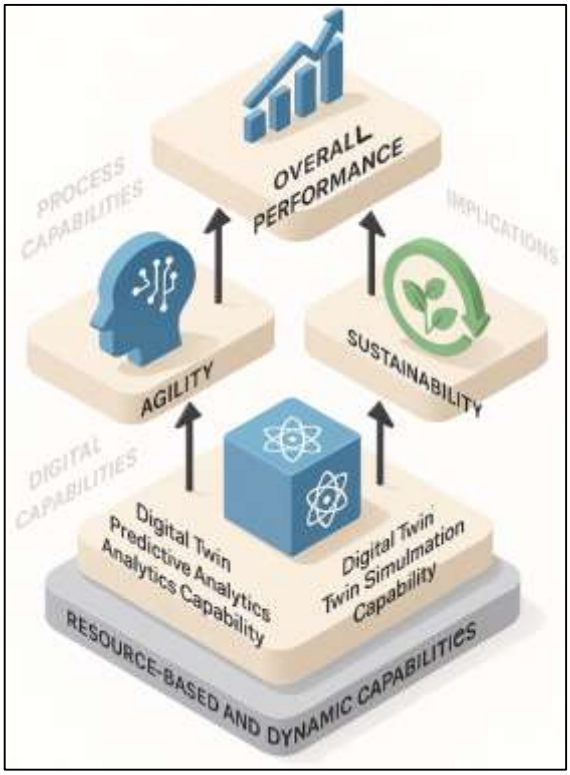
**DISCUSSION**

The findings of this study have shown a consistent and statistically strong pattern: organizations reporting higher levels of AI-based predictive analytics capability and digital twin simulation capability have also reported significantly higher supply chain agility, sustainable supply chain performance, and overall supply chain performance. On a five-point Likert scale, mean scores for AI and digital twin capability have been above the neutral midpoint, and the regression models have explained a substantial share of variance in agility ($R^2 = 0.463$), sustainability ($R^2 = 0.417$), and overall performance ($R^2 = 0.589$). These results have suggested that, in practice, AI-driven forecasting, anomaly detection, and optimization routines, together with digital twin–based simulation, have not been peripheral add-ons but embedded elements of day-to-day planning and execution. The significant standardized coefficients for AI capability ($\beta = 0.42$ for agility; $\beta = 0.37$ for sustainability) and digital twin capability ($\beta = 0.29$ for agility; $\beta = 0.26$ for sustainability) have indicated that both technologies have meaningfully shaped how quickly and responsibly supply chains have been able to respond to demand and supply volatility. At the same time, agility ($\beta = 0.31$) and sustainability ($\beta = 0.28$) have emerged as central predictors of overall performance, with digital capabilities retaining smaller yet still significant direct effects. This pattern has confirmed the core logic of the conceptual framework: AI-based predictive analytics and digital twins have mattered both in their own right and through the agile and sustainable practices they have enabled, aligning with the study's objectives of demonstrating both direct and mediated pathways from digital capability to performance.

When compared with earlier work on analytics-enabled supply chains, the current findings have extended and reinforced several established themes. Prior studies have shown that business analytics and big data capabilities have been associated with higher supply chain performance and competitive advantage, particularly when embedded in robust process orientations (Trkman et al., 2010). The present results have supported these conclusions by showing that AI-based predictive analytics

capability has correlated strongly with performance outcomes and has retained a significant effect even after controlling for agility and sustainability. Similarly, research on big data and predictive analytics in logistics has highlighted positive effects on forecasting accuracy, inventory optimization, and responsiveness (Waller & Fawcett, 2013). The relatively high mean scores for agility and overall performance, together with the strong AI–agility relationship, have suggested that such mechanisms have been active in the surveyed organizations. At the same time, the current study has gone beyond many earlier contributions by explicitly modeling sustainability as a parallel outcome and mediator. Whereas earlier work has often treated sustainability as a secondary or separate objective (Hazen et al., 2016), the significant links from AI and digital twin capability to sustainable supply chain performance have indicated that data-driven tools have been used to monitor and improve environmental and social indicators alongside cost and service metrics. In this respect, the findings have answered calls from sustainable supply chain research to integrate digital technologies into triple-bottom-line frameworks rather than treating "green" initiatives as stand-alone projects (Carter & Rogers, 2008).

**Figure 10: Proposed Framework for future study**




The results related to digital twin simulation capability have also complemented and extended prior work on cyber-physical systems and virtual supply chains. Earlier studies have conceptualized digital twins as high-fidelity virtual representations of assets and processes, updated with real-time data, and emphasized their potential for scenario analysis, capacity planning, and risk evaluation (Monostori, 2014). Case-based contributions have shown how digital twins can mirror plant operations or in-house logistics to support performance improvement (Coelho et al., 2020) or create virtual supply chains constructed from enterprise models (Matsuda et al., 2020). The current study has been among the first to quantify, using Likert-based survey data and regression models, how perceived digital twin capability has related to both agility and sustainability outcomes at the supply chain level. The significant β coefficients for digital twin capability in the agility and sustainability models have suggested that organizations have used these virtual environments not only to test throughput, layouts, or routing policies, but also to support faster reconfiguration and to evaluate environmental and social impacts of network changes. Moreover, the partial mediation pattern where digital twin capability has influenced performance both directly and via agility and sustainability has aligned with the idea that

digital twins function as integrative platforms, bringing together physical data, predictive models, and decision rules in ways that reshape how supply chains sense and respond to change (Büyüközkan & Göçer, 2018). In contrast to more technically focused digital twin studies, which have often stopped at architectural descriptions or isolated case demonstrations (Melesse et al., 2020), this research has provided systematic evidence that digital twin investments reported by practitioners have been linked to broad, perceived performance benefits.

The practical implications of these findings have been especially salient for senior leaders, including supply chain executives, chief information officers, and enterprise or solution architects who have been responsible for designing secure, scalable, and value-generating digital infrastructures. First, the magnitude of the relationships has indicated that AI and digital twins have yielded the strongest benefits when they have been treated as end-to-end capabilities spanning data capture, integration, analytics, simulation, and decision execution, rather than as stand-alone tools. Architecturally, this has meant investing in clean, governed data pipelines from IoT devices, transactional systems, and external data sources into shared analytical and simulation environments (Choi et al., 2018). For CISOs and security architects, the results have implied that these pipelines must have been designed with robust cybersecurity, access control, and data integrity safeguards, because agility and sustainability gains have depended on trusting the quality and timeliness of data flowing into predictive models and digital twins. From an operational standpoint, the partial mediation effects have shown that technology alone has not been sufficient: agile and sustainable processes have been critical channels translating digital capability into performance. Thus, managers have needed to complement AI and digital twin deployments with redesign of planning processes, cross-functional collaboration routines, and governance mechanisms that have embedded model outputs in routine decision-making. For sustainability leaders, the positive links between digital capabilities and sustainable performance have suggested that integrating carbon, energy, and social indicators into analytics dashboards and twin scenarios has been a practical way to make sustainability constraints visible and actionable during planning and network design. Overall, the findings have pointed toward a joint agenda for CIOs, CISOs, and supply chain leaders: build secure and interoperable data and simulation architectures, and simultaneously institutionalize agile and sustainability-oriented practices that can exploit these digital resources in everyday decisions.

Theoretically, the study has refined and extended resource-based and dynamic capabilities perspectives in the context of digitally enabled, sustainable supply chains. Resource-based theory has emphasized that valuable, rare, inimitable, and non-substitutable resources underpin competitive advantage (Barney et al., 2011), while dynamic capabilities theory has stressed the importance of sensing, seizing, and reconfiguring in turbulent environments (Teece, 2007). The empirical results have suggested that AI-based predictive analytics capability and digital twin capability have functioned as such higher-order resources, because they have enabled organizations to sense demand and supply changes, to evaluate options virtually, and to reconfigure sourcing, production, and logistics more effectively. By explicitly modeling agility and sustainability as mediating capabilities, the study has shown how these digital resources have been translated into operational and sustainability outcomes, and then into overall performance, offering a concrete "capability pipeline" from data infrastructure to strategic advantage. This complements earlier work that has linked IT and analytics capabilities to agility and performance (Liu et al., 2013), but typically without explicitly incorporating digital twins or sustainability outcomes. The results have also aligned with and extended theories of sustainable supply chain management, which have argued that coherent bundles of practices across sourcing, operations, and logistics underlie exemplary sustainability performance (Pagell & Wu, 2009)). Here, AI and digital twins have been positioned not just as tools but as integral elements of those practice bundles, enabling more informed configuration choices and continuous re-optimization. Conceptually, the significant indirect effects via agility and sustainability have supported a view of digitalized supply chains as layered systems in which digital capabilities, process capabilities, and performance outcomes have been tightly coupled, suggesting promising avenues for further theory development around digitally enabled, agile, and sustainable capability portfolios.

At the same time, several methodological and contextual limitations have needed to be revisited when

interpreting these contributions. The cross-sectional design has meant that the study has captured associations at a single point in time, rather than dynamic trajectories of capability development and performance change. Although the patterns have been consistent with causal interpretations digital capabilities leading to agility, sustainability, and performance the possibility of reverse causality or reciprocal relationships cannot have been ruled out, as high-performing firms might also have been more able to invest in AI and digital twins (Huo et al., 2019). The non-probability, purposive sampling strategy has focused on organizations that have already engaged with AI and digital twin technologies, which has implied that the findings have been most applicable to digitally progressive firms. Less digitally mature organizations, or those in sectors with different regulatory or competitive pressures, might have exhibited different patterns of relationships. The reliance on self-reported Likert-scale measures has introduced the potential for common method bias and social desirability bias, as respondents might have overestimated the sophistication of their capabilities or the strength of their sustainability performance (Pagell & Wu, 2009). While good reliability and factorial validity indices have mitigated concerns about measurement quality, the constructs have still reflected perceptions rather than objective metrics. Finally, the study has not incorporated detailed structural information about supply chain configurations, such as network topology or contract structures, which might have interacted with digital capabilities to shape agility and sustainability outcomes (Fosso Wamba et al., 2018). These limitations have not undermined the core findings but have indicated that they should be interpreted as evidence of robust perceived relationships in a specific, digitally active sample, rather than as definitive causal estimates generalizable to all supply chains.

Building on these limitations, several directions for future research have been suggested by the study's findings. Longitudinal designs could have followed firms over time as they have implemented AI-based predictive analytics and digital twin platforms, tracking changes in agility, sustainability, and performance to provide stronger evidence about causality and temporal ordering. Multi-source data, combining survey responses with objective indicators such as lead-time variability, stock-out rates, emissions data, and audited sustainability performance, could have reduced common method bias and offered a more granular view of how digital capabilities have interacted with operational metrics (Hazen et al., 2014). Future studies might also have incorporated more detailed structural variables for example, centralization vs. decentralization of decision rights, the density of supplier networks, or the presence of blockchain-based traceability systems to understand how network design and governance have conditioned the value of AI and digital twins (Queiroz et al., 2019). From a modeling standpoint, structural equation modeling or multi-level approaches could have explored more complex relationships, such as non-linear effects, threshold behaviors, or differences between focal firms and their partners. Finally, qualitative or mixed-method research could have opened the "black box" of implementation, documenting how organizations have overcome organizational resistance, data quality issues, and cybersecurity concerns when integrating AI and digital twins into mission-critical supply chain processes (Arunachalam et al., 2018; Baryannis et al., 2019). By addressing these avenues, future research has the potential to deepen the understanding of how AI-based predictive analytics and digital twin simulation can be orchestrated, secured, and governed to support truly agile, sustainable, and resilient supply chains.

## CONCLUSION

This study has set out to examine how AI-based predictive analytics capability and digital twin simulation capability have been associated with agile and sustainable supply chain management and, in turn, with overall supply chain performance, and the evidence generated has strongly supported this central proposition. Using survey data from 214 professionals across manufacturing, logistics, and retail/service organizations and Likert's five-point scales, the research has shown that both AI-based predictive analytics and digital twin capabilities have been present at moderate to high levels and that supply chain agility, sustainable supply chain performance, and overall performance have all been rated positively. Reliability and factor analyses have confirmed that the constructs have been measured in a robust and internally consistent way, which has allowed the hypotheses to be tested with confidence. Correlation and regression analyses have revealed that AI-based predictive analytics capability and digital twin capability have each had significant and positive effects on supply chain agility and sustainable supply chain performance, while models explaining overall performance have

demonstrated that agility and sustainability have been powerful predictors in their own right. Importantly, AI and digital twin capabilities have retained smaller but still significant direct effects on overall performance when agility and sustainability have been included in the models, and mediation analysis has confirmed that agility and sustainability have partially mediated the relationships between digital capabilities and performance. Taken together, these findings have indicated that organizations with stronger AI and digital twin capabilities have not only reacted faster and more flexibly to demand and supply changes but have also reported better environmental and social outcomes and higher overall supply chain performance. Conceptually, the study has contributed by operationalizing AI-based predictive analytics and digital twin simulation as supply chain–level capabilities and by embedding them within a resource-based and dynamic capabilities framework that has linked digital resources to agility, sustainability, and performance through clearly specified pathways. Practically, the results have highlighted that senior supply chain, IT, and sustainability leaders have needed to treat AI and digital twins as end-to-end socio-technical capabilities supported by clean data pipelines, secure architectures, cross-functional collaboration, and explicit sustainability metrics rather than as isolated pilot tools if they have wanted to unlock their full value. At the same time, the research has acknowledged limitations related to its cross-sectional, self-reported, and purposively sampled design, which has constrained causal inference and broad generalizability, and has suggested that longitudinal, multi-source, and more structurally detailed studies will be needed to further validate and refine the proposed relationships. Nonetheless, within these boundaries, the study has achieved its objectives by providing coherent quantitative evidence that AI-based predictive analytics and digital twin simulation capabilities have played a central role in enabling agile and sustainable supply chains and have thereby contributed to superior perceived performance in complex, digitally transforming supply chain environments.

**RECOMMENDATIONS**

Based on the findings of this study, several practical recommendations can be offered for managers, digital leaders, and policy makers who aim to build agile and sustainable supply chains through AI-based predictive analytics and digital twin simulation. First, organizations should treat AI and digital twins as strategic capabilities, not one-off technology projects: this means developing a clear digital supply chain roadmap that links analytics and simulation investments directly to agility and sustainability objectives, such as faster response to demand volatility, reduced waste, lower emissions, and improved social compliance. Second, firms should prioritize data quality and governance by establishing standardized data models, clear ownership of key data sets, and robust processes for cleaning, validating, and securing data, because predictive models and digital twins are only as reliable as the data that feed them. Third, senior leaders should build cross-functional teams that bring together supply chain, operations, IT, data science, and sustainability experts to co-design use cases, interpret model outputs, and embed insights into planning cycles; this helps avoid the common gap where analytics and simulation outputs remain technically impressive but operationally unused. Fourth, organizations are encouraged to invest systematically in skills and change management, including training managers to understand the logic and limitations of AI and twin-based recommendations, and supporting frontline staff as processes, KPIs, and decision rights are adjusted to reflect more agile and sustainability-oriented ways of working. Fifth, digital twin environments should be leveraged as experimentation sandboxes in which alternative network designs, sourcing strategies, transportation modes, and inventory policies can be tested not only for cost and service level but also for environmental and social impacts before any physical changes are implemented, thus reducing risk and accelerating innovation. Sixth, CIOs and CISOs should ensure that AI and digital twin platforms are embedded in secure, resilient architectures, with appropriate access controls, monitoring, and contingency plans, so that greater data sharing and connectivity do not create unacceptable cyber or privacy vulnerabilities. Seventh, firms should start with focused, high-value pilot projects (for example, predictive demand planning for a volatile product line, or a digital twin of a critical distribution center), but design these pilots with scalability in mind, identifying the reusable components data pipelines, models, governance structures that can be extended across the wider supply chain. Finally, industry associations, regulators, and educational institutions are encouraged to support this transformation by promoting common data standards, offering training and certification in digital supply chain

competencies, and incentivizing investments that demonstrably enhance both agility and sustainability. Taken together, these recommendations emphasize that the full benefits of AI-based predictive analytics and digital twin simulation will be realized only when organizations integrate technology, process design, governance, and human capabilities into a coherent, long-term program for agile and sustainable supply chain excellence.

**LIMITATIONS**

The present study has been subject to several limitations that need to be acknowledged when interpreting its findings and considering their generalizability. First, the research has employed a cross-sectional survey design, capturing perceptions of AI-based predictive analytics capability, digital twin capability, agility, sustainability, and performance at a single point in time. As a result, the analysis has not been able to establish strict causal relationships or to observe how changes in digital capability have translated into evolving agile and sustainable practices over months or years; reverse or reciprocal causality (for example, high-performing firms investing more in AI and digital twins) may also have been present but not captured. Second, the study has relied on non-probability purposive sampling of organizations that have already engaged, at least to some extent, with AI and digital twin initiatives. While this has been appropriate for accessing knowledgeable respondents, it has meant that the sample has not been statistically representative of all firms or sectors, particularly those at early stages of digitalization or operating in less data-intensive environments. Third, all constructs have been measured using self-reported Likert's five-point scales from single respondents per organization (or per unit), which has introduced the risk of common method variance and social desirability bias; respondents may have overestimated the sophistication of their digital capabilities or the strength of their sustainability performance, and their views may not have fully reflected the diversity of perspectives within their organizations. Fourth, the study has focused on perceived capabilities and outcomes rather than on objective indicators such as detailed system logs, implementation budgets, real-time performance metrics (for example, lead-time variability, on-time delivery, energy use, emissions), or externally audited sustainability reports, which could have provided more granular and independently verified assessments of the relationships under investigation. Fifth, the statistical modeling has relied on linear regression and mediation analysis, assuming linear relationships and additive effects among variables; potential non-linearities, thresholds, or interaction effects for instance, complementarities between AI and digital twins at high adoption levels, or moderating influences of network complexity, regulatory pressure, or organizational culture have not been explicitly modeled. Sixth, the constructs for AI-based predictive analytics and digital twin capability have been treated as relatively broad, composite variables, meaning that the study has not distinguished between different types or maturity levels of AI and digital twin solutions (for example, basic reporting vs. advanced machine learning, deterministic simulation vs. fully synchronized cyber-physical twins), which may have distinct implications for agility and sustainability. Finally, the empirical setting has been limited to a subset of sectors (primarily manufacturing, logistics, and retail/service) and to organizations willing to participate in a relatively detailed survey, which has implied that contextual factors such as national regulations, industry structure, and supply chain power dynamics may have constrained the generalizability of the findings to other domains such as public sector logistics, agriculture, or highly regulated healthcare supply chains. These limitations have not invalidated the study's main conclusions, but they have indicated that the results should be interpreted as indicative, perception-based evidence within a specific digitally active context, and they have highlighted the need for complementary longitudinal, multi-method, and multi-context research to build a more comprehensive understanding of AI- and digital twin–enabled agile and sustainable supply chains.

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