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AI-Enhanced What-If Scenario Analysis in Supply Chain Digital Twins: A Multi-Objective Trade-Off Perspective on Cost, Resilience, and Carbon Efficiency

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Abstract

Global supply chains face compounding disruptions driven by geopolitical tensions, tariff volatility, climate events, and demand uncertainty. Digital twin technology, which creates dynamic virtual replicas of physical supply chain networks, has emerged as a promising instrument for proactive decision-making through simulation and scenario analysis. This paper presents an analytical framework examining how artificial intelligence enhances What-If scenario analysis within supply chain digital twin environments, with a particular focus on multi-objective trade-offs among cost, resilience, service level, and carbon efficiency. By synthesizing recent literature, publicly available datasets, and U.S. federal supply chain digitalization initiatives, the study delineates the mechanisms through which AI enables multi-source data integration, automated scenario generation, cascading disruption prediction, and Pareto-optimal decision evaluation within digital twin architectures. Rather than proposing a new computational model or system implementation, this work offers a structured analytical perspective that bridges the gap between isolated single-module optimization studies and the integrated cross-functional decision-making that modern supply chains demand. The findings highlight a convergent relationship between resilience optimization and carbon reduction, and identify key technical and organizational challenges for practical implementation at the enterprise level.

Keywords: *supply chain digital twin, artificial intelligence, What-If scenario analysis, multi-objective optimization*

1. Introduction

1.1 Background: Growing Complexity and Vulnerability of Global Supply Chains

The contemporary global supply chain landscape is characterized by a structural shift from isolated, low-frequency disruptions to compounding, multi-source shocks propagating across interconnected networks. The cascading nature of these shocks—where a tariff adjustment in one region triggers shortages in another, which then propagate into labor and logistics inefficiencies downstream—has rendered linear, sequential response paradigms fundamentally inadequate. Ivanov and Dolgui [1] conceptualized the supply chain digital twin as a real-time computerized representation of network states, emphasizing its role in transitioning risk management from reactive response to predictive control. Their work highlighted that combining model-based and data-driven approaches is essential for uncovering interrelations among risk data, disruption modeling, and performance assessment within the Industry 4.0 context. Ivanov [2] further documented how the COVID-19 pandemic fundamentally transformed supply chain resilience research, revealing that traditional planning paradigms were inadequate when facing prolonged, overlapping crises that simultaneously disrupted demand patterns, supplier capacity, and global logistics infrastructure.

Quantitative evidence underscores this escalating vulnerability. According to the Resilience 2024 Global Disruption Report, Tier 1 and Tier 2 manufacturers experienced nearly 90% more supply interruptions compared to 2020, with average recovery times extending by over one month (Source: Resilience, Inc., 2024). The McKinsey 2024 Trade Sensitivity Index reported that tariff-related policy fluctuations eroded global manufacturing margins by 3–5% over a two-year period (Source: McKinsey & Company, 2024).

1.2 The Emergence of AI-Powered Supply Chain Digital Twins

Digital twin technology has evolved from product-level replicas in manufacturing to network-level dynamic representations encompassing entire supply chain ecosystems. The global digital twin market reached USD 24.97 billion in 2024 and is projected to grow at a CAGR of 34.2%, reaching approximately USD 155.84 billion by 2030 (Source: Grand View Research, 2024). Within the United States, the market generated USD 6.41 billion in 2024, with projections of USD 34.19 billion by 2030 at a CAGR of 30.7% (Source: Grand View Research, 2024). The AI in logistics and supply chain market was valued at approximately USD 20.1 billion in 2024, projected to reach USD 196.6 billion by 2034 at a CAGR of 25.9% (Source: Industry Market

Research, 2024). Badakhshan and Ball [3] demonstrated the practical value of applying digital twins for inventory and cash management under disruptions, providing empirical evidence that simulation-driven What-If analysis can materially improve supply chain financial performance during crisis periods. The convergence of AI capabilities with digital twin architectures enables a qualitatively new mode of supply chain decision-making: one that is anticipatory, multi-dimensional, and continuously adaptive.

1.3 Research Scope, Objectives, and Paper Organization

This paper investigates the following question: How can AI enhance What-If scenario analysis within supply chain digital twin environments to enable multi-objective trade-off decisions across cost, resilience, service level, and carbon efficiency? Badakhshan and Ball [4] advanced hybrid modelling approaches integrating simulation and analytical methods to support digital twin-based master planning under disruptions. Building on this trajectory, the present study does not propose a new computational model; it offers an analytical framework synthesizing current knowledge, contextualizing the discussion within publicly available data and U.S. policy initiatives, and identifying both opportunities and challenges. Section 2 reviews relevant literature. Section 3 presents the core analytical framework. Section 4 discusses policy context, practical implications, and implementation challenges. Section 5 provides concluding remarks.

2. Literature Review

2.1 Digital Twin Technology in Supply Chain Management: Concepts and Evolution

The conceptual foundations of supply chain digital twins have undergone significant evolution over the past decade, progressing through distinct phases of increasing sophistication. Zheng, Lu, and Kiritsis [5] articulated the vision of cognitive digital twins—systems incorporating reasoning, learning, and autonomous decision-making capabilities beyond passive mirroring. Their framework identified challenges including semantic interoperability, knowledge representation, and heterogeneous data integration, positioning cognitive digital twins as the next frontier beyond conventional simulation-based approaches. Freese and Ludwig [6] addressed the absence of a specialized application framework by developing a multi-layered architecture outlining dimensions including coverage scope (internal versus external supply chain), actor involvement (shippers, freight forwarders, manufacturers), asset granularity (product, shipment, facility), and technology dependencies, providing structured guidance for early-phase adoption by supply chain planners and operators. A key distinction that emerges from this literature is the difference between product-centric digital twins, which model the geometry and lifecycle of individual items, and network-level supply chain digital twins, which must capture dynamic relationships among multiple echelons, stochastic demand patterns, transportation networks, and financial flows—all updating in near-real time. This distinction carries significant implications for both the data architecture and the AI capabilities required to support What-If scenario analysis.

2.2 AI-Driven Decision Optimization in Supply Chains

Artificial intelligence has been applied across virtually every supply chain segment, from demand sensing and inventory positioning to logistics routing and supplier risk assessment. Ivanov [7] proposed a formal model for supply chain resilience drawing from immune system analogies, distinguishing among innate strategies (structural redundancy, process flexibility), passive adaptive strategies (pre-existing backup plans), and active adaptive strategies (dynamic resource reallocation, expedited shipping). This biological metaphor provides a useful lens for understanding how AI can serve different resilience functions within a digital twin environment—functioning as both the immune memory that recognizes known threat patterns and the adaptive response system generating novel countermeasures for previously unseen disruptions. The quantified impact of AI adoption in supply chain operations has been documented across multiple industry benchmarks. McKinsey reports that early AI adopters achieve approximately 15% lower logistics costs and 35% improved inventory levels (Source: McKinsey & Company, 2024). The Gartner 2025 Resilience Benchmark found that companies embedding AI-driven risk metrics achieved 28% faster response rates and 19% shorter recovery cycles compared to organizations relying on manual contingency management (Source: Gartner, 2025). A 2024 survey also indicated that 97% of manufacturing CEOs planned to deploy AI in operations within two years (Source: Industry Survey, 2024), signaling a rapidly approaching inflection point for enterprise-wide adoption.

2.3 Research Gaps: The Need for Integrated What-If Scenario Analysis

Despite these advances, two specific gaps remain underexplored. Ashraf, Eltawil, and Ali [8] advanced disruption detection for cognitive digital supply chain twins using hybrid deep learning, demonstrating that convolutional and recurrent neural networks can identify emerging disruptions from multivariate sensor data. Their work focused on the detection phase rather than the downstream What-If reasoning and multi-objective evaluation that would follow detection within an integrated decision framework. Wasi, Islam, and Akib [9] introduced SupplyGraph, a real-world benchmark dataset modeling supply chain elements as graph structures, showing that GNN-based models outperformed conventional approaches by 10–30% in regression and classification tasks. Their contribution addressed the data infrastructure gap but did not extend to the scenario simulation and trade-off analysis layers.

The overarching gap that persists is the systematic integration of these capabilities—data fusion, AI-driven scenario generation, cascading effect prediction, and multi-objective evaluation—within the What-If analysis paradigm of supply chain digital twins. This paper addresses this integrative gap through a structured analytical framework.

3. Analytical Framework: AI-Enhanced What-If Scenario Analysis in Supply Chain Digital Twins

3.1 Multi-Source Data Integration Layer for Digital Twin Construction

The foundation of any supply chain digital twin lies in its ability to ingest, harmonize, and continuously update data from heterogeneous sources. Ivanov and Gusikhin [10] documented the large-scale digital twin implementation at Ford Motor Company, demonstrating that practical challenges of data integration—including latency, format inconsistency, and access permissions—often outweigh the algorithmic challenges of optimization. Their case study revealed that Ford, operating 37 plants globally and consuming 17 billion parts annually across up to ten supplier tiers, required a systematic framework for multi-source data harmonization before any meaningful scenario analysis could be conducted. Table 1 presents a taxonomy of multi-source data categories for constructing an AI-ready supply chain digital twin.

Table 1. Multi-Source Data Categories for Supply Chain Digital Twin Construction

Data Category	Typical Source Systems	Key Variables	Update Frequency
Operational transaction data	ERP, WMS, TMS	Order volume, inventory levels, shipment status, lead times	Real-time to hourly
Demand and market signals	POS systems, CRM, web analytics	Sales velocity, promotional calendars, price elasticity	Daily to weekly
IoT and sensor data	RFID, GPS, temperature sensors	Asset location, environmental conditions, utilization rates	Real-time (streaming)
External disruption signals	News feeds, weather APIs, geopolitical indices	Disaster alerts, port congestion, trade policy changes	Event-driven
Financial and compliance data	Accounting systems, customs databases	Landed costs, tariff rates, carbon tax obligations	Weekly to monthly

The U.S. Department of Transportation’s Freight Logistics Optimization Works (FLOW) initiative exemplifies this paradigm at a national scale. Launched in 2022, FLOW now encompasses 85 member organizations—including major retailers, ocean carriers, and port authorities—that share logistics data to build a forward-looking view of U.S. supply chain capacity against projected demand (Source: BTS, FLOW Program, 2024). The platform collects data spanning importer purchase orders, port throughput, rail terminal capacity, and warehouse end-destination information.

Figure 1. Analytical Framework for AI-Enhanced What-If Scenario Analysis in Supply Chain Digital Twins

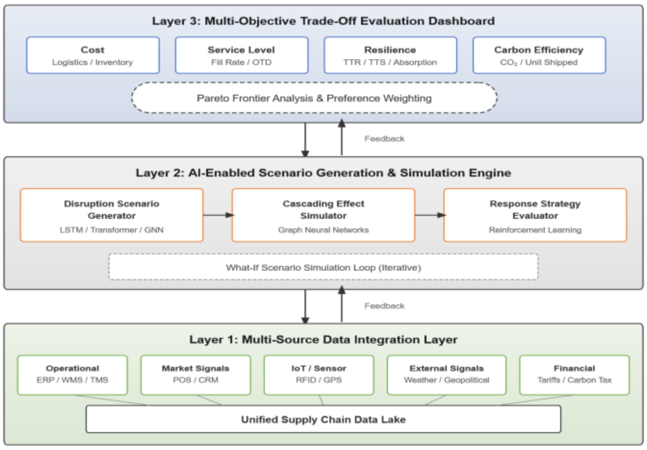

Figure 1 illustrates the three-layer framework proposed in this paper. The bottom layer represents the Multi-Source Data Integration Layer aggregating operational, market, IoT, external, and financial data streams. The middle layer depicts the AI-Enabled Scenario Generation and Simulation Engine, where machine learning models generate disruption scenarios, predict cascading effects, and evaluate response strategies. The top layer presents the Multi-Objective Trade-Off Evaluation Dashboard assessing Pareto-optimal solutions across cost, service level, resilience, and carbon efficiency. Bidirectional arrows between layers indicate continuous feedback loops enabling dynamic model updating.

3.2 AI-Enabled Scenario Generation and Simulation for What-If Analysis

The What-If analysis capability distinguishes supply chain digital twins from conventional business intelligence tools. Prathapage, Ivanov, and Ivanova [11] provided a comprehensive review of supply chain stress testing, identifying that effective tests require disruption scenario definitions, a simulation engine propagating shocks through the network, and performance indicators capturing both impact and recovery dynamics. They found that combining qualitative (expert-driven) and quantitative (computational) methods yields the most robust outcomes.

AI enhances each component in distinct ways. Table 2 maps specific AI techniques to their functional roles within the What-If process.

Table 2. AI Techniques for What-If Scenario Generation in Supply Chain Digital Twins

AI Technique	Functional Role in SCDT	Input Requirements	Output Characteristics
Graph Neural Networks	Network-level demand propagation, supplier dependency modeling	Graph-structured topology, node-level time series	Spatially-aware forecasts, hidden link detection
LSTM Networks	Temporal demand pattern recognition, anomaly detection	Historical demand sequences, seasonal indicators	Time-series forecasts with uncertainty quantification
Reinforcement Learning	Dynamic response strategy evaluation	State representations, action spaces, reward functions	Optimal policy recommendations for inventory/routing
Hybrid Deep Learning (CNN+RNN)	Multi-modal disruption detection	Sensor signals, text alerts, operational metrics	Early warning classifications with confidence scores
Transformer-based Models	Long-range dependency capture across echelons	Extended sequences, cross-echelon feature sets	Context-aware predictions of global chain state

Figure 2. AI-Driven What-If Scenario Generation Workflow in Supply Chain Digital Twins

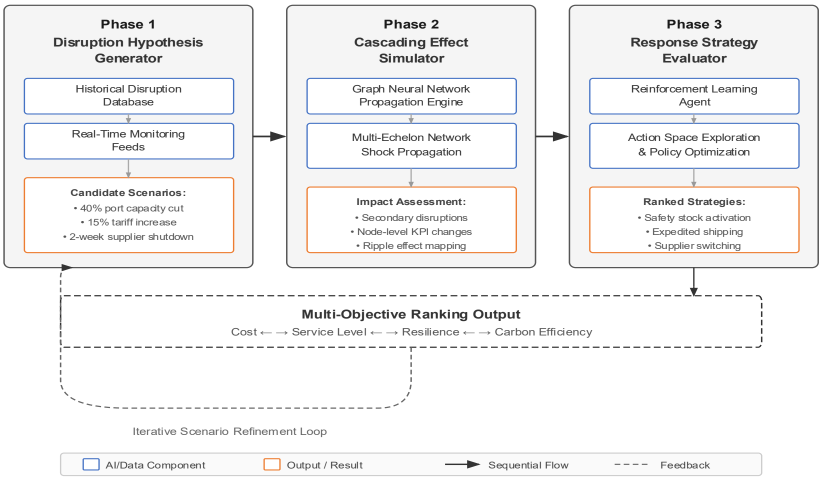

Figure 2 depicts the sequential workflow of AI-driven scenario generation. The process begins with a Disruption Hypothesis Generator using historical disruption databases and real-time monitoring to propose candidate scenarios—a 40% port capacity reduction, a 15% tariff increase on semiconductor components, or a two-week supplier shutdown due to extreme weather. Each scenario enters a Cascading Effect Simulator powered by graph neural networks that propagate the initial shock through multi-echelon networks. The final stage involves a Response Strategy Evaluator employing reinforcement learning agents that test mitigation actions—safety stock activation, expedited shipping, supplier switching, demand prioritization—and rank them according to multi-objective criteria.

Industry evidence corroborates this capability: Siemens models over 500 production scenarios daily within its digital twin environment, achieving 20% downtime reduction and 14% logistics cost volatility decrease (Source: Supply Chain Management Review, 2025). Toyota's resilience intelligence hub detected a semiconductor disruption six weeks before materialization, enabling preemptive order reallocation (Source: Supply Chain Management Review, 2025).

3.3 Multi-Objective Trade-Off Evaluation: Cost, Resilience, Service Level, and Carbon Efficiency

The value of What-If analysis is realized through its capacity to illuminate trade-offs among competing objectives. Malekzadeh and Torabi [12] developed a digital twin for resilience analysis under immediate and long-term disruptions, demonstrating through a plastic manufacturing case study that the intersection of economic downturns with pandemic crises poses substantial collapse risk—reinforcing the necessity of multi-objective evaluation.

Table 3 presents the KPI framework for evaluating What-If scenarios within supply chain digital twins.

Table 3. Multi-Objective KPI Framework for SCDT What-If Scenario Evaluation

Objective Dimension	**Key Performance Indicators**	**Benchmark Values**	**Data Source**
Cost Efficiency	Total logistics cost, landed cost per unit, inventory carrying cost	AI adopters: ~15% lower logistics costs	McKinsey & Company, 2024
Resilience	Time-to-recover, time-to-survive, disruption absorption rate	AI-embedded firms: 28% faster response, 19% shorter recovery	Gartner, 2025
Service Level	Order fill rate, on-time delivery rate, perfect order percentage	Target: ≥95% on-time delivery	Industry standard benchmarks
Carbon Efficiency	CO_2 per unit shipped, carbon intensity per tonne-km	Resilience optimization reduced carbon intensity by 12%	Schneider Electric case, 2025

Empirical evidence suggests a convergent relationship between resilience optimization and carbon reduction. Schneider Electric's multi-tier AI digital twin for Asia-Pacific operations simultaneously diversified ports, balanced lead times, and automated inventory allocation. The resilience-oriented optimization unexpectedly reduced carbon intensity per unit shipped by 12%, demonstrating that operational efficiency from intelligent resource allocation benefits both resilience and sustainability metrics (Source: Supply Chain Management Review, 2025).

Figure 3. Conceptual Illustration of Multi-Objective Pareto Trade-Off Space: Cost, Resilience, and Carbon Efficiency

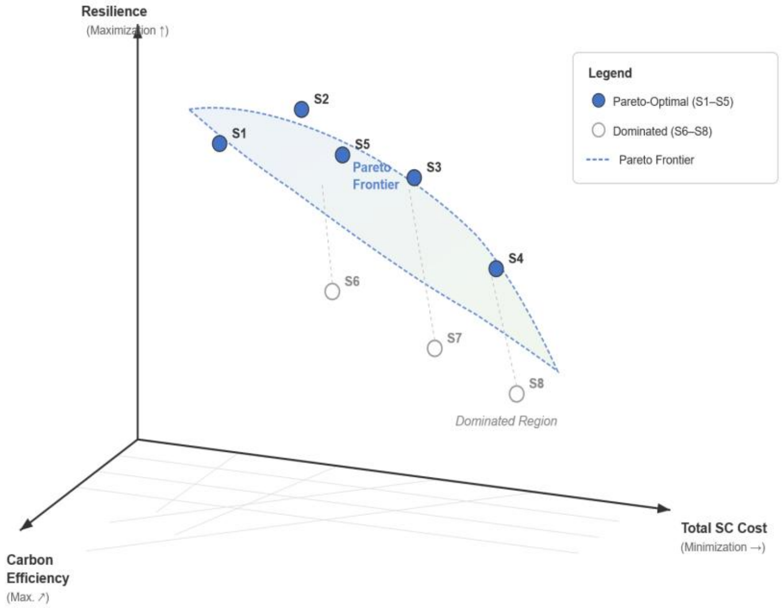

Figure 3 presents a three-dimensional Pareto trade-off space with axes representing total supply chain cost (minimization), resilience index (maximization), and carbon efficiency (maximization). The Pareto frontier surface delineates non-dominated solutions where improving one objective requires compromising another. Scenario outcomes S1 through S8 are plotted as points, with dominated solutions below the frontier and optimal solutions on the surface. Decision-makers navigate this space by applying preference weights reflecting organizational priorities, regulatory requirements, and stakeholder expectations. Critically, this surface is not static—as conditions evolve, the AI components continuously re-evaluate the frontier, providing a living trade-off map.

4. Discussion: Policy Context, Practical Implications, and Challenges

4.1 U.S. Policy Landscape: FLOW, NIST Standards, and Supply Chain Resilience Initiatives

The framework presented in this paper operates within a policy environment increasingly supportive of supply chain digitalization. Ivanov [13] extended the intelligent digital twin concept toward digital supply chain ecosystems, arguing that future management will require interconnected ecosystems enabling automatic model generation and collaborative scenario analysis across organizational boundaries—a vision aligning with U.S. federal policy trajectory.

Three federal initiatives are particularly relevant. Table 4 summarizes these programs.

Table 4. U.S. Federal Initiatives Supporting Supply Chain Digital Twin Development

Initiative	Lead Agency	Launch	Current Scale	Primary Focus
FLOW	USDOT / BTS	2022	85 member organizations	Freight data sharing, supply-demand visibility
Digital Twins for Advanced Manufacturing	NIST	2024	Standards development	Measurement science, open standards (ISO 23247)
Digital Thread Roadmap	NIST (GCR 24-057)	2024	Cross-industry roadmap	Traceability, interoperability, resilience

Thomas [14] conducted a NIST economic analysis estimating the potential annual impact of full digital twin adoption across U.S. manufacturing at USD 37.9 billion. A Monte Carlo simulation varying key parameters produced a 90% confidence interval of USD 16.1 billion to USD 38.6 billion, with a median of USD 27.2 billion annually (Source: NIST AMS 100-61, 2024). The BTS Supply Chain and Freight Indicators portal publishes real-time data across port congestion, freight movement, transportation labor, and capacity tightness—providing open-access infrastructure supporting the data integration layer described in Section 3.1 (Source: BTS, Freight Indicators, 2025).

4.2 Practical Implications for Enterprise Decision-Making

Holterman et al. [15] developed a roadmap for strengthening U.S. manufacturing supply chains through digital thread technology, identifying end-to-end data traceability and interoperability standards as foundational prerequisites. Their roadmap emphasized that organizational readiness—workforce digital literacy, cross-functional data governance, and executive commitment—is as critical as technical infrastructure for realizing the full value of digital twin deployments.

In the domain of inventory management, the transition from traditional reorder-point policies to predictive multi-echelon optimization within a digital twin represents a substantial capability upgrade. The U.S. Bureau of Labor Statistics documented a greater than 30% increase in warehousing wages between July 2020 and July 2024 (Source: BLS, 2024), which amplifies the cost penalty associated with suboptimal inventory decisions—whether in the form of excessive safety stock tying up working capital or insufficient stock leading to lost sales and expedited replenishment costs. AI-enhanced What-If analysis allows inventory planners to simulate demand variability, lead time fluctuations, and warehouse capacity constraints simultaneously, identifying safety stock configurations that minimize total holding costs while maintaining target service levels across the distribution network.

In logistics operations, the shift from static route planning to dynamic, scenario-driven dispatch optimization carries measurable financial and environmental impact. Organizations leveraging AI-powered logistics tools report approximately 15% reductions in freight costs through route optimization, mode selection, and consolidation strategies informed by real-time network conditions (Source: McKinsey & Company, 2024). The What-If capability adds a strategic dimension to these operational gains: planners can pre-evaluate the cost and carbon implications of rerouting through alternative corridors, switching between ocean and rail modes, or redistributing volumes across distribution centers before committing resources. The Schneider Electric case provides particularly instructive evidence—resilience-oriented investments including port diversification and lead time balancing simultaneously reduced carbon intensity by 12%, suggesting that integrated optimization within digital twins reveals synergies that siloed functional analyses would miss (Source: Supply Chain Management Review, 2025). This finding challenges the prevalent organizational assumption that resilience and sustainability represent competing budget priorities, and points toward a more integrated investment evaluation methodology enabled by the multi-objective framework described in Section 3.3.

4.3 Technical and Organizational Challenges for Implementation

Data interoperability remains the most persistent technical barrier to realizing the analytical framework at enterprise scale. Supply chain data resides across dozens of heterogeneous systems—ERP platforms from different vendors, proprietary warehouse management systems, carrier-specific tracking APIs, and disparate IoT protocols—each with distinct data schemas, update cadences, and access controls. The absence of universally adopted data exchange standards means that a significant portion of digital twin implementation effort is consumed by integration engineering rather than analytical development. The Catena-X initiative in the European automotive sector and the FLOW platform in the U.S. freight domain represent early attempts to address this challenge through industry-specific data-sharing standards, but broader adoption remains in its nascent stages.

The fidelity-cost trade-off in digital twin construction presents an additional challenge that requires careful calibration. Higher-fidelity twins that model individual SKU-level inventory movements, lane-level transportation costs, and facility-level capacity constraints demand substantially greater computational resources and data maintenance effort. The NIST economic analysis identified that determining appropriate levels of accuracy, precision, and flexibility involves evaluating incremental costs and benefits of each input and output dimension (Source: NIST AMS 100-61, 2024). Organizations must calibrate their digital twin granularity to match their decision scope—strategic network design decisions may tolerate lower fidelity with broader geographic and temporal coverage, while tactical inventory decisions at specific distribution centers demand high fidelity at the node level.

Organizational transformation constitutes the third critical challenge. The value of AI-enhanced What-If analysis is realized only when decision-making processes are restructured to consume and act upon scenario-based insights. This requires moving from sequential, department-specific planning toward integrated cross-functional scenario review where procurement, logistics, finance, and sustainability teams jointly evaluate trade-off options. The shift from deterministic planning toward scenario-aware planning represents a fundamental change in organizational decision-making philosophy that demands sustained executive sponsorship, new performance metrics, and revised meeting structures.

5. Conclusion

5.1 Summary of Key Findings

This paper has presented an analytical framework for understanding how AI enhances What-If scenario analysis within supply chain digital twin environments. The framework delineates three integrated layers—

multi-source data integration, AI-enabled scenario generation and simulation, and multi-objective trade-off evaluation—that collectively enable supply chain decision-makers to transition from reactive, single-objective optimization toward proactive, multi-dimensional strategic planning. The analysis identified that the trade-off landscape among cost, resilience, service level, and carbon efficiency is not characterized by uniform conflict; empirical evidence from industrial implementations indicates convergent opportunities where resilience-oriented optimization simultaneously yields carbon efficiency gains. The discussion situated this framework within the U.S. policy context, demonstrating alignment with federal initiatives including the FLOW freight data-sharing platform, NIST digital twin standards for advanced manufacturing, and the digital thread technology roadmap for manufacturing supply chains.

5.2 Limitations of the Current Study

Several limitations merit acknowledgment. This paper offers an analytical framework and knowledge synthesis rather than empirical validation through computational experiments or real-world system deployment. The data points and industry benchmarks cited throughout the analysis are drawn from publicly available reports and secondary sources; direct access to proprietary enterprise supply chain data would enable more granular validation of the proposed framework components and allow quantitative testing of the trade-off dynamics described in the Pareto analysis. The discussion of policy context and practical implications is primarily oriented toward the U.S. supply chain landscape, and the applicability of specific institutional mechanisms to other national or regional contexts requires separate examination. The multi-objective trade-off analysis presented in Section 3.3 is conceptual in nature; the precise shape and dynamics of the Pareto surface are contingent on industry-specific cost structures, network topologies, and regulatory environments that vary significantly across sectors and geographies. These constraints should be considered when interpreting the framework's applicability to specific operational contexts.

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