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The Role of Digital Twins in Supply Chain Process Simulation and Optimization

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ABSTRACT: Supply chains are increasingly exposed to disruption, demand volatility, and operational complexity that traditional planning tools cannot fully capture in real time. Digital twin technology is emerging as a powerful capability for process simulation and optimization by creating a continuously updated virtual representation of supply chain operations. A digital twin combines physical process data, enterprise system transactions, and predictive analytics to simulate scenarios, evaluate trade-offs, and recommend optimal decisions before execution. This paper explores the role of digital twins in improving supply chain performance through simulation-based planning, bottleneck identification, inventory optimization, transportation network design, and resilience building. The study synthesizes research and industry frameworks to evaluate enabling technologies, implementation approaches, governance requirements, and barriers such as data quality, integration complexity, and organizational change. The findings indicate that digital twins can deliver measurable improvements in service levels, throughput, and cost efficiency by enabling decision-makers to evaluate outcomes under multiple conditions, including disruptions. However, value realization depends on strong master data, integration with ERP and IoT sources, and continuous model validation. The paper concludes with recommendations for implementing digital twins as an operational capability rather than a one-time transformation project.

KEYWORDS: Digital twin, supply chain simulation, process optimization, scenario planning, predictive analytics, Industry 4.0, resilience

I. INTRODUCTION

Modern supply chains operate in an environment of uncertainty and constant change. Volatile demand, global sourcing dependencies, fluctuating capacity, transportation delays, and supplier reliability issues now drive frequent planning failures across industries. Disruptions are no longer rare exceptions but routine conditions that leaders must anticipate. This exposes a major weakness in traditional planning approaches: many tools are built for stable conditions, while real operations are fundamentally unstable.

Although ERP platforms provide strong transactional control and visibility across orders, inventory, procurement, and execution, they often fall short as decision-support systems under uncertainty. Designed primarily for execution discipline rather than end-to-end simulation, they leave decision-makers relying on static models, spreadsheets, and deterministic logic that assumes consistent lead times and predictable constraints. In reality, supply chains behave like complex adaptive systems, where small disruptions can cascade into large service failures, cost escalation, or inventory imbalance.

This challenge is amplified by growing network interdependence. Most supply chains operate within ecosystems of suppliers, contract manufacturers, logistics providers, distribution nodes, and last-mile partners. Decision-making is further complicated by partial visibility, inconsistent stakeholder data, and constraints that change faster than planning cycles can respond. More digital connectivity does not automatically reduce complexity it increases the burden of converting data into actions that improve service, cost, and resilience simultaneously.

Digital twin technology has emerged as a promising solution for supply chain simulation and optimization. A digital twin is not just a dashboard or analytics layer, but a continuously updated virtual representation of processes, assets, and decision rules that mirrors real operational behavior. By integrating real-time data streams with process models and advanced analytics, digital twins enable scenario-based simulation and safe evaluation of alternatives before changes are implemented. Unlike conventional planning systems that generate a single plan based on fixed assumptions, digital twins support multi-scenario exploration and trade-off analysis, shifting planning from reactive problem-solving to predictive decision-making.

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Originally developed for manufacturing and product lifecycle management, digital twins are rapidly expanding into logistics and end-to-end planning due to Industry 4.0 adoption. Advances in IoT data availability, cloud-scale computing, and AI analytics have made it feasible to build twins that operate continuously and deliver recommendations grounded in current conditions. In practice, they support decisions at strategic, tactical, and operational levels from network design and capacity planning to inventory optimization, disruption forecasting, and execution adjustments.

This paper examines how digital twins enable supply chain simulation and optimization, outlines the architecture required for adoption, and discusses barriers such as data quality, integration complexity, model governance, and organizational uptake. The goal is to present a structured view of how digital twin capabilities strengthen decision-making by moving supply chains from reactive management toward predictive, simulation-driven optimization and continuous improvement.

II. DIGITAL TWIN CONCEPT AND EVOLUTION

Digital twin technology refers to the integration of a physical system and its digital representation through data-driven synchronization (Grieves & Vickers, 2017). While earlier simulation models were typically static or periodically updated, a digital twin is designed to be continuously refreshed using real-world signals such as operational events, sensor data, and enterprise transactions. This continuous synchronization is critical because it shifts simulation and analysis from “planning in theory” to “planning based on operational reality,” enabling decisions to reflect real constraints rather than assumptions.

A key distinction emphasized in the digital twin literature is that a twin is not just a visualization model but a behavioral replica that captures system logic and cause-effect relationships. In this sense, the twin can represent how a supply chain will respond under variable conditions such as demand spikes, lead-time disruptions, or bottleneck accumulation. A continuously updated twin becomes a practical decision asset because it improves the credibility of simulation results for real-time operational planning (Kritzinger et al., 2018).

Tao, Qi, Liu, and Kusiak (2018) emphasize that digital twins play a foundational role in “smart manufacturing” by combining real-time data, modeling logic, and analytics into a unified decision-support structure. Over time, the scope of digital twins has evolved significantly. The first generation focused on engineering applications such as product performance modeling, lifecycle design, and predictive maintenance. Later, digital twins expanded to process-level twins in manufacturing operations, where production flow, machine status, and throughput could be simulated. Most recently, research and practice have increasingly shifted toward operational digital twins, where the objective is to model entire operational environments, including logistics networks, inventory flows, supplier behavior, and multi-echelon planning outcomes (Fuller et al., 2020).

In supply chain management, this evolution is particularly important because the “system” is not a single asset, but a distributed network consisting of suppliers, manufacturers, warehouses, transport routes, and demand channels. Therefore, the value of a supply chain digital twin depends not only on modeling accuracy but also on its ability to represent interdependencies and trade-offs across the full network.

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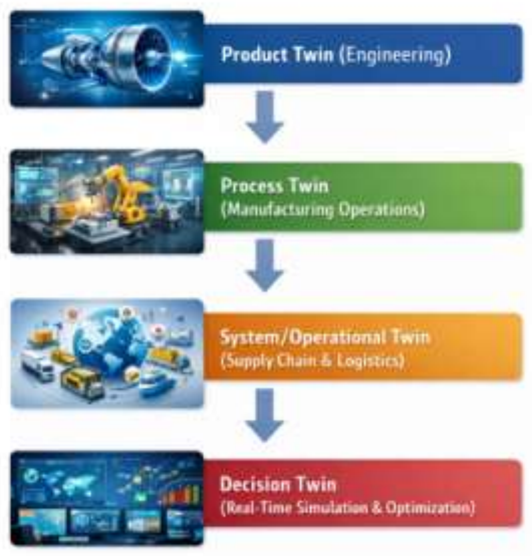
Figure 2.1: Evolution of Digital Twins



2.1 Simulation as a Decision Support Capability in Supply Chains

Simulation has been widely used in supply chain research and operations planning for decades, particularly through discrete-event simulation, agent-based simulation, and system dynamics. These methods help managers understand the behavior of complex systems and evaluate policies such as replenishment logic, production scheduling rules, labor deployment strategies, and distribution capacity scenarios.

Negri, Fumagalli, and Macchi (2017) highlight that the core value of digital twins lies in combining physical data with operational logic in a way that strengthens the reliability of simulated outcomes. When simulation reflects real operational conditions and constraints, it becomes not only academically interesting but operationally actionable. This improves adoption because operational stakeholders are more likely to trust results that match what they see in the real world.

From a decision-support viewpoint, this creates an important shift. Conventional planning often assumes a "single future" based on a forecast and fixed lead times. Digital twins instead enable planners to simulate multiple plausible futures and understand how policies perform under variability. This is increasingly necessary in environments where disruptions are not exceptional events but frequent occurrences.

2.2 Digital Twins and Supply Chain Optimization

Optimization in supply chain management typically involves balancing competing objectives such as cost efficiency, service levels, throughput, and risk exposure. Classical supply chain optimization techniques often rely on deterministic assumptions and stable process parameters, including fixed lead times, consistent capacity availability, and predictable transportation performance. In reality, these assumptions frequently break down due to demand volatility, supplier instability, and logistics uncertainty.

Digital twins strengthen optimization because they integrate simulation and optimization into one decision environment. Instead of optimizing based on simplified assumptions, the twin can simulate actual operational conditions and then evaluate optimization decisions across multiple scenarios. This allows managers to quantify trade-offs rather than relying on single-point estimates.

Ivanov and Dolgui (2020) argue that digital supply chain twins can improve resilience significantly by enabling organizations to model disruptions, test recovery policies, and redesign processes with a clear understanding of system-level ripple effects. Rather than reacting after service failures occur, organizations can use digital twins to pre-test mitigation strategies (alternate sourcing, inventory reallocation, route changes, or priority sequencing) before disruptions escalate.

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This simulation-driven approach is particularly valuable in today's supply chain environment because it supports decision-making under uncertainty, where the future cannot be represented by a single set of conditions. Instead, resilience depends on understanding performance across many possible outcomes, including extreme but plausible disruption cases.

2.3 Enabling Technologies for Digital Twins

The literature consistently emphasizes that digital twins are not created through a single technology. Instead, they depend on an ecosystem of integrated systems and data flows. In supply chains, the digital twin typically requires the following enabling components:

1. ERP systems (transactional truth)

ERP platforms provide structured enterprise data including procurement transactions, demand signals (sales orders), inventory balances, planning parameters, and financial constraints. ERP data often acts as the "system of record," defining the baseline truth for operational planning and compliance.

2. IoT sensors and operational event data (execution visibility)

IoT technologies support visibility into asset condition, throughput performance, machine utilization, energy usage, location tracking, and real-time status of logistics resources. Although IoT is not mandatory for every supply chain twin, it becomes essential in environments requiring real-time operational control, such as automated warehouses, smart factories, or temperature-sensitive cold chain networks.

3. Cloud platforms (scalability and performance)

Cloud environments support scalable computation, faster scenario modeling, and centralized data storage required for running multiple simulation cycles across large networks. Cloud computing also enables continuous refresh cycles, which are difficult to maintain with traditional on-premise simulation deployments (Fuller et al., 2020).

4. AI and machine learning (prediction and anomaly detection)

Machine learning methods enhance digital twins by improving forecasting accuracy, detecting anomalies, predicting ETAs, and identifying patterns that static business logic may miss. However, the literature also cautions that AI outputs require governance and validation, especially when decisions have financial or operational risk implications.

5. Optimization engines (decision recommendations)

Optimization solvers (linear programming, mixed-integer programming, heuristic and metaheuristic approaches) are often paired with digital twins to convert simulation insight into recommended actions. Without optimization logic, the twin may identify what could happen but not necessarily recommend the best action.

Kritzinger et al. (2018) describe digital twins as a convergence of simulation, real-time connectivity, and systems integration. Importantly, most research indicates that the effectiveness of a digital twin depends less on its visual interface and more on the completeness of its integration and the reliability of the underlying models. A visually impressive twin that lacks accurate process logic or robust data pipelines can quickly lose credibility among decision-makers.

III. DIGITAL TWIN ARCHITECTURE FOR SUPPLY CHAIN SIMULATION

A functional supply chain digital twin requires more than a visualization dashboard or a one-time simulation model. To deliver consistent value, a digital twin must operate as a continuously updated decision-support system that reflects the real supply chain, simulates alternative scenarios, and recommends actions that improve cost, service, throughput, and resilience. The architecture of a supply chain digital twin can be represented through four core layers: the Physical Layer, Data Layer, Model Layer, and Decision and Execution Layer. Together, these layers enable end-to-end representation of operational behavior and allow planning decisions to be tested under realistic constraints rather than simplified assumptions.

3.1 Physical Layer

The physical layer represents the real-world supply chain environment and includes all entities, assets, and processes that the digital twin aims to replicate and optimize. This typically includes operational nodes and resources such as:

- manufacturing plants and production lines
- warehouses and distribution centers
- suppliers and contract manufacturers
- transportation fleets and third-party logistics partners
- retail outlets, fulfillment centers, and end customers

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In practical supply chains, each physical entity introduces constraints that influence overall performance. For example, a factory may have limited capacity due to labor availability, setup time, maintenance schedules, or yield variation. Similarly, warehouses may face dock congestion, storage limitations, pick/pack productivity challenges, or shifting order patterns. Transportation networks add additional complexity through delivery time variability, lane constraints, carrier capacity, and route congestion.

The physical layer is important because it defines what the twin must ultimately represent: **the flow of goods, information, and constraints across interconnected processes**. Without a clear definition of the physical scope, a digital twin risks becoming fragmented or overly narrow, limiting its ability to support network-level decision-making. A supply chain twin must therefore reflect both the physical structure (nodes and lanes) and the operational behavior (rules and constraints) that drive day-to-day performance.

3.2 Data Layer

The data layer forms the connective tissue between physical operations and the digital twin. It is responsible for collecting, cleansing, validating, and transmitting operational signals so that the twin can remain synchronized with real system conditions. This layer typically includes structured and semi-structured data from multiple sources such as:

- ERP transactions: sales orders, purchase orders, inventory balances, planning parameters, supplier lead times, receipts, and production orders
- WMS logs: inbound receiving activity, put away completion, replenishment moves, picking waves, packing performance, cycle counts, and shipment staging
- TMS tracking: carrier tender acceptance, shipment status, freight cost, delivery delays, ETA updates, and lane performance
- IoT and telemetry signals: machine status, equipment uptime, temperature and location tracking, asset utilization, throughput rates, and automated system events
- External risk feeds: weather conditions, port congestion, geopolitical events, natural disasters, and regulatory disruptions

The quality and timeliness of these signals directly influence the accuracy and usefulness of the digital twin. Poor master data, inconsistent units of measure, missing timestamps, or duplicate transaction entries can introduce distortion into simulation and optimization outcomes. In supply chain environments, this often becomes one of the biggest barriers to twin effectiveness because operational performance is highly sensitive to parameters such as lead time, demand variability, and capacity constraints. Even a small mismatch between data reality and model assumptions can result in poor recommendations and reduced user trust.

From an architectural perspective, the data layer must also manage challenges such as:

- integrating data across systems that were not designed to connect easily
- handling different refresh rates (real-time IoT vs. periodic ERP updates)
- maintaining governance over data ownership and definitions
- ensuring consistency across suppliers, sites, and regions

In this sense, the data layer is not merely a technical connector but a foundational requirement for reliable decision-making. When a digital twin fails, the cause is often not the simulation engine but the underlying data foundation. Therefore, establishing data governance and master data reliability is essential for digital twins to function as a dependable operational capability.

3.3 Model Layer

The model layer is the intelligence core of the digital twin. It is responsible for converting data into behavior by representing how the supply chain operates under constraints and variability. This layer contains simulation logic, predictive models, and decision rules that allow planners to evaluate system behavior before implementing changes in real operations.

A supply chain twin typically includes the following categories of models:

(a) Simulation Models

Simulation models replicate the movement of inventory and resources through supply chain processes. Common approaches include:

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- Discrete event simulation, often used for warehouses, production flow, and logistics execution processes, where events such as picking completion, replenishment, loading, or machine changeovers influence throughput and queue formation
- Network simulation, used for multi-echelon planning, distribution flows, transportation lane constraints, and end-to-end service level modeling

Simulation is especially valuable because it captures non-linear behavior and constraint interactions. For example, warehouse productivity is not simply additive; congestion and task contention can reduce sharply when utilization is near capacity. Digital twins allow these system interactions to be tested under different operational conditions.

(b) Predictive Models
Predictive models strengthen digital twins by estimating the likelihood and impact of future conditions, such as:
- demand forecasts and demand sensing adjustments
- lead-time prediction under supplier variability
- ETA prediction based on transportation and lane behavior
- failure probability modeling for equipment and critical resources
- risk scoring models for disruption probability

These predictive models are particularly relevant in supply chains where uncertainty is high, and decisions must be made before complete information is available.

(c) Business Rules and Constraints
A supply chain twin must incorporate operational decision logic, such as:
- replenishment policies (reorder points, safety stock, min/max levels)
- customer service constraints (priority rules, lead time promises, allocation logic)
- production constraints (batch sizes, setup times, labor rules)
- transportation rules (consolidation thresholds, mode selection)
- compliance requirements (temperature controls, regulated goods constraints)

These rules determine how the system behaves in practice. Without them, the twin becomes a theoretical model rather than an operational replica. Including business rules is especially important because many supply chain decisions are policy-driven rather than purely mathematical.

3.4 Decision and Execution Layer

The decision and execution layer represents the output and action component of the digital twin. This layer converts simulation insights and predictive signals into optimization recommendations that decision-makers can implement through planning or execution systems. Typical optimization outcomes include:
- dynamic adjustment of reorder points, safety stock, and allocation policies
- production resequencing to reduce changeovers and avoid shortages
- supplier switching recommendations during risk events or constraints
- transportation rerouting and mode switching under lane disruption
- order prioritization decisions when supply is constrained
- capacity rebalancing across plants or distribution centers

A mature digital twin architecture integrates directly with execution systems to allow actions to be automated or semi-automated. In this setup, the twin does not merely recommend actions but can trigger workflows, alerts, and approvals through connected platforms such as ERP, WMS, and TMS. For example, if the twin predicts a high risk of stockout for critical SKUs, it can recommend expedited replenishment or alternate sourcing, then initiate a planning proposal or exception workflow.

However, this layer also introduces governance and accountability requirements. Decisions must be traceable, explainable, and aligned with the organization’s decision rights. Without clear governance, organizations may hesitate to execute recommendations, limiting the twin to analysis only and reducing realized benefits.

3.5 Digital Twins as Decision Systems (Not Visualization Tools)

A key theme in the literature is that digital twins create value only when they operate as decision systems rather than passive visualization platforms. Many organizations build “control tower dashboards” that show metrics and alerts but do not support scenario testing or optimization recommendations. Digital twins go beyond this by enabling decision-makers to answer the more critical question: What action should we take, and what will happen if we take it?

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Digital twins also become more valuable over time when they are designed with continuous learning cycles. This means that after recommendations are executed, outcomes are captured and compared against predicted performance. The twin can then be recalibrated to improve forecasting accuracy, refine simulation parameters, and strengthen future recommendations. This continuous validation cycle is essential because supply chain conditions evolve, and static models quickly lose relevance.

Ultimately, the architecture of a supply chain digital twin must support three capabilities simultaneously:
1. Operational fidelity (accurate representation of constraints and flows)
2. Decision relevance (outputs connected to real decisions and KPIs)
3. Continuous improvement (feedback loops and ongoing model calibration)

When these conditions are met, the digital twin becomes a scalable operational capability that improves performance and resilience across planning horizons, rather than a one-time transformation output.

IV. APPLICATIONS OF DIGITAL TWINS IN SUPPLY CHAIN OPTIMIZATION

Digital twins are increasingly adopted as a practical decision-support capability in supply chains because they allow organizations to test operational decisions under real constraints before executing them in the physical system. Unlike traditional planning approaches that depend on fixed assumptions and periodic refresh cycles, supply chain digital twins enable simulation-driven optimization by continuously synchronizing with execution data from ERP, WMS, TMS, MES, and IoT sources. This synchronization allows digital twins to represent operational variability more accurately, including demand volatility, lead time uncertainty, capacity limitations, labor constraints, and logistics disruptions (Ivanov & Dolgui, 2020).

As organizations pursue agility and resilience, the value of digital twins becomes most visible when they are applied to high-impact optimization areas such as bottleneck identification, inventory planning, transportation design, disruption response, and sustainability performance improvement.

4.1 Process Bottleneck Identification and Throughput Improvement

A frequent supply chain challenge is that operational constraints are not always visible at the planning level. Many bottlenecks emerge dynamically due to resource contention, delayed inbound materials, labor shortages, equipment failures, and unplanned demand surges. These bottlenecks are rarely static. Instead, they shift over time across processes such as receiving, put away, picking, staging, packing, production line changeovers, or outbound loading. When organizations rely only on standard KPIs or periodic operational reporting, bottlenecks may remain hidden until performance degradation becomes visible through service failures, rising backlog, missed production schedules, or escalated expediting costs.

Digital twins address this issue by enabling organizations to simulate end-to-end process flows and identify where throughput constraints occur under varying demand and capacity conditions. In a warehouse context, a twin can simulate order arrival patterns, pick density, slotting design, labor assignment, and dock scheduling. In manufacturing, it can evaluate machine utilization, changeover sequencing, routing constraints, and yield variation. These simulations allow managers to determine whether bottlenecks are driven by true physical constraints (e.g., dock doors, conveyor capacity, machine uptime) or by process design issues (e.g., unbalanced waves, poor replenishment rules, excessive travel time, or manual approvals).

4.2 Inventory Optimization and Service Level Balancing

Inventory optimization remains one of the most persistent challenges in supply chain management because it sits at the intersection of cost, service, and risk. Many organizations still operate with static replenishment policies, fixed safety stock levels, or planning parameters that are updated infrequently. These approaches often assume relatively stable demand, predictable lead times, and consistent supplier performance. In practice, demand volatility and supply uncertainty make static policies increasingly ineffective, leading either to excess inventory and working capital waste or to stockouts that damage service levels and customer trust.

Digital twins improve inventory planning by simulating service-level outcomes under realistic conditions, including demand shifts, lead-time variability, supplier reliability patterns, capacity constraints, and transportation delays. Rather than treating inventory as a single-point decision, a digital twin models inventory as a dynamic control mechanism that must absorb variability across the network. This allows the twin to test policies such as:

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- Reorder point changes
- dynamic safety stock logic
- minimum order quantities vs. service outcomes
- postponement strategies
- prioritization rules for constrained supply
- substitution rules across SKUs

A major advantage is that inventory optimization is rarely local. In multi-echelon networks, the performance of one node affects upstream and downstream outcomes. For example, increasing safety stock at a regional distribution center may reduce stockouts locally but increase demand variability for upstream manufacturing. Similarly, holding inventory at a central hub may reduce overall inventory but worsen responsiveness for customers requiring shorter lead times. Digital twins enable multi-echelon simulation to measure these trade-offs with more realism, supporting better segmentation decisions such as which products need high availability, which can tolerate longer lead times, and which require redundancy due to supply risk.

4.3 Transportation and Distribution Network Optimization

Transportation and distribution networks represent a high-cost and high-variability layer of supply chain operations. Even when production and inventory planning are well-structured, logistics variability can cause significant disruptions due to route congestion, carrier capacity shortages, driver availability issues, port delays, weather events, and shifting fuel costs. Traditional transportation planning often focuses on execution-level efficiency: load consolidation, route selection, carrier tenders, and freight auditing. However, many logistics decisions are deeply interconnected with upstream decisions such as inventory positioning, order promising rules, and warehouse throughput availability.

This simulation capability becomes especially valuable in balancing the trade-offs between cost efficiency and responsiveness. For example, air freight may improve responsiveness during disruption but create unsustainable cost spikes. Ocean freight may reduce cost but increase exposure to long-lead uncertainty. Digital twins enable planners to quantify such trade-offs with scenario-driven analysis instead of relying on static assumptions.

V. IMPLEMENTATION CHALLENGES AND PRACTICAL BARRIERS

Despite strong interest in digital twins as a next-generation capability for supply chain simulation and optimization, many implementations fail to scale beyond pilot programs. In practice, digital twin value is not driven only by simulation sophistication, but by an organization’s ability to sustain high-quality data, maintain integration reliability, build user trust, and continuously validate model behavior. This section outlines the most common implementation barriers, emphasizing that digital twins represent both a technical architecture challenge and an organizational operating model transformation.

5.1 Data Quality, Data Governance, and Master Data Integrity

A supply chain digital twin is only as reliable as the data feeding it. Digital twins depend on continuous data pipelines to remain synchronized with the real supply chain, and weak data foundations quickly lead to inaccurate simulation results. When simulation outputs do not match operational reality, decision-makers lose confidence and revert to manual judgment, spreadsheets, or traditional deterministic planning methods. This trust breakdown is one of the most common reasons digital twins fail to deliver sustained value.

Even when simulation logic is robust, missing or inconsistent master data can invalidate results. Supply chain master data is particularly sensitive because it defines the structure, rules, and constraints of the system. Common master data issues that degrade twin accuracy include:

- Incorrect or outdated lead times (supplier lead time vs. actual replenishment behavior)
- Incomplete or inconsistent BOM structures (especially in multi-level manufacturing)
- Inaccurate routings and work center capacities (cycle time, yields, setup times)
- Location hierarchies and network mappings that do not represent real operational flow
- Units of measure inconsistencies (case vs. each vs. pallet conversion errors)
- Planning parameters like MOQ, order multiples, safety stock, reorder points
- Supplier performance data gaps, including variability and reliability measures

Liang et al. (2022) emphasize that trustworthy analytics and AI systems depend heavily on high-quality datasets, and this principle applies directly to supply chain digital twins. In digital twin programs, data governance must be treated as

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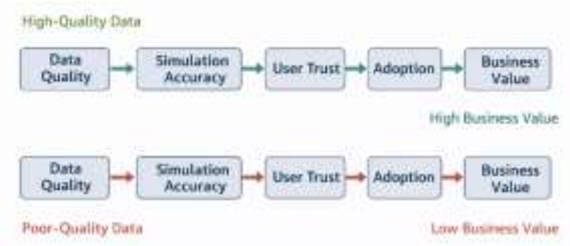
a core capability rather than an IT clean-up activity. This requires explicit ownership of master data domains, consistent definitions across functions, and periodic audits to ensure alignment between system parameters and operational reality.

Figure 5.1 "Data Quality Impact on Digital Twin Reliability"



A simple progression illustrating how poor data quality creates low trust, low adoption, and low ROI.

5.2 Integration Complexity Across Systems

Supply chain data is distributed across multiple systems, each designed for different process ownership and operational scope. ERP platforms capture transactional truth, WMS manages warehouse execution, TMS captures transportation planning and shipment events, and MES or production systems capture manufacturing behavior. In many organizations, these platforms do not share consistent data definitions or integration timing. As a result, building a unified data model to support real-time simulation becomes a significant challenge.

Integration complexity emerges from several factors:

(a) Multi-system fragmentation

A digital twin cannot operate effectively if it only reflects ERP-level "planned truth." The twin must incorporate execution reality such as:

- actual shipment departure times vs. planned times
- real picking throughput vs. standard labor productivity
- real production output vs. scheduled production quantities
- actual supplier delivery performance vs. contractual lead time

To capture these differences, the twin requires integration across planning and execution systems, including continuous reconciliation of discrepancies.

(b) Data latency and refresh mismatches

Different systems operate on different refresh cycles:

- IoT and telemetry may refresh in seconds
- TMS events may update every few minutes
- ERP transactions may post hourly or daily depending on design

A digital twin must handle these mismatches without creating inconsistent system state or misleading simulation outcomes.

(c) External partner integration

Many supply chain constraints originate outside the enterprise boundary, including supplier delays, carrier capacity changes, port congestion, and third-party warehouse operations. Integrating partner signals introduces added complexity because data may be unavailable, unreliable, or commercially sensitive.

Kritzinger et al. (2018) note that digital twin maturity is directly linked to integration capability and connectivity. Without connected data flows, a digital twin loses its primary advantage: synchronization with real operations. In such cases, it becomes a static simulation model that requires manual updates, leading to the same adoption limitations that traditional simulation tools face.

Organizations often underestimate the effort required for integration because the challenge is rarely limited to technical connectivity alone. It also involves establishing consistent business definitions, mapping event logic across platforms, and reconciling operational differences across geographies and business units.

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5.3 Organizational Adoption and Change Management

Even when the technical architecture is strong, digital twins frequently fail due to organizational barriers. Digital twins challenge traditional decision-making behaviors by shifting planning from deterministic outputs (a single plan) toward probabilistic outcomes (scenario ranges, likelihoods, trade-offs). For many supply chain teams, this requires a significant mindset shift.

Several adoption challenges commonly appear:

Resistance to algorithmic recommendations

Planners and operations leaders may resist simulation-driven decisions because:

results feel like "black box outputs", recommendations challenge local experience or intuition, accountability feels unclear when outcomes are uncertain, the organization is culturally conditioned to deterministic plans.

5.4 Model Validation and Continuous Improvement Requirements

Digital twins are not "build once and run forever." They must be continuously validated and recalibrated to maintain accuracy and stakeholder confidence. Unlike static planning tools, a digital twin is expected to mirror real system behavior under changing conditions. If operational outcomes diverge from simulation predictions, leaders begin to distrust the model's recommendations, and adoption declines quickly.

Validation is essential because supply chain conditions change continuously due to:

- evolving demand patterns
- supplier performance changes
- lane reliability shifts in transportation networks
- new SKUs and product lifecycle changes
- warehouse process redesigns
- labor productivity variation
- process policy updates (allocation rules, order cutoffs, batching logic)

Therefore, a digital twin must support iterative calibration methods such as:

- tracking differences between predicted vs. actual service level results
- monitoring forecast accuracy over time and by product segment
- measuring actual vs. modeled lead time distributions
- validating constraint behavior (capacity, throughput, queue patterns)
- updating process parameters as operations change

Continuous validation makes a digital twin closer to an operational capability than a one-time deployment. This also affects governance: organizations need defined ownership for "model maintenance," similar to how ERP systems require configuration governance. Without this discipline, the digital twin becomes outdated and loses credibility.

In mature organizations, validation becomes a routine process, such as:

- weekly performance reconciliation
- monthly parameter recalibration
- quarterly model revision cycles
- post-disruption scenario tuning

This is what enables the twin to remain relevant, scalable, and trusted as supply chain conditions evolve.

VI. "TEST BEFORE ACTING": THE DECISION ADVANTAGE

In traditional supply chain environments, decisions are often made using a mix of historical averages, simplified assumptions, and local experience. Plans may look feasible in planning tools, yet fail in execution because variability is not captured accurately. For example, a plan may assume a 10-day supplier lead time, but real lead times might range from 8 to 25 days depending on capacity and transportation conditions. Similarly, a warehouse might appear to have sufficient labor based on standard productivity rates, while real throughput changes significantly due to order mix and congestion.

Digital twins change this by enabling pre-execution scenario testing, where planners can evaluate the effect of a decision under multiple operating conditions.

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6.1 From Rules-Based Decisions to Evidence-Based, Scenario-Driven Optimization

What digital twins fundamentally changes is the logic of supply chain decision-making. Many supply chain organizations still operate using rules-based planning, such as fixed safety stock formulas, static reorder points, fixed cycle stock strategies, and deterministic replenishment assumptions. These methods are efficient in stable environments but increasingly fragile when conditions fluctuate.

Digital twins shift the organization toward evidence-based planning, where decisions are supported by simulation results rather than fixed rules alone. The most important transformation here is that the supply chain begins to move from "one plan" thinking to scenario-driven optimization.

Instead of optimizing for the most likely case only, a supply chain twin allows planners to evaluate decisions across:

6.2 Improving Supply Chain Performance: What Changes in Outcomes

Digital twins influence performance in a measurable way, not by making supply chains "perfect," but by enabling better trade-offs and faster adaptation. In practical terms, digital twins commonly improve performance across these dimensions:

1) Service performance becomes more reliable

Digital twins help organizations protect service levels by identifying weak points before they become failures, such as impending stockouts, overstressed lanes, or throughput constraints.

2) Cost performance becomes more controlled

Rather than reacting with expensive expediting once problems occur, digital twins support proactive decisions such as inventory redistribution, early capacity rebalancing, and smarter mode selection.

3) Throughput becomes more stable and predictable

Through simulation, organizations can see how congestion and constraint accumulation will form, enabling earlier intervention.

4) Resilience becomes measurable instead of aspirational

Instead of treating resilience as a vague objective, digital twins enable stress-testing and comparison of recovery options.

5) Planning becomes faster and less dependent on heroics

A well-run digital twin reduces reliance on manual planning labor, repeated meetings, and last-minute overrides. Decision cycles become shorter because outcomes are visible earlier and can be tested quickly.

VII. CONCLUSION

Digital twins represent a significant shift in how supply chains can be simulated, optimized, and managed under uncertainty. Unlike traditional planning tools that rely on static assumptions and periodic refresh cycles, supply chain digital twins provide a continuously updated virtual representation of operational reality. This capability enables organizations to test decisions before execution, evaluate trade-offs under multiple scenarios, and identify performance risks early enough to prevent downstream failures. Across the applications discussed in this paper, digital twins show potential to improve throughput, service reliability, inventory positioning, transportation efficiency, and disruption readiness by transforming supply chain management from reactive problem-solving to predictive, simulation-driven optimization.

However, the evidence also indicates that digital twins are not a guaranteed performance accelerator simply because they are technologically advanced. The effectiveness of a digital twin depends on the maturity of the organization's operational discipline and foundational data environment. Weak master data, fragmented integration across systems, unclear decision rights, and limited model validation quickly reduce twin credibility, limiting adoption and preventing measurable business value. In practical terms, the organizations most likely to succeed are those that treat digital twins as an operational capability embedded into recurring planning and execution cycles, rather than a one-time transformation project.

7.1 Summary of Key Findings

Based on the synthesis of research and practitioner-oriented frameworks, this paper highlights several core findings:

- Digital twins improve decision quality more than they automate tasks. The largest advantage is the ability to simulate outcomes under realistic constraints and uncertainty, enabling higher confidence decision-making.
- Simulation-driven planning enables faster response and higher resilience. Digital twins allow organizations to evaluate worst-case and high-risk scenarios, making resilience measurable and operational rather than theoretical.

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- Data governance and system integration determine twin credibility. Without high-quality master data and reliable execution connectivity, a twin becomes stale and loses adoption.
- A digital twin must be continuously validated to stay trusted. Ongoing calibration is required to align simulated outputs with real system behavior as conditions change.
- Business value increases when digital twins are embedded into daily operations. Sustainable benefits emerge when twins become part of planning governance, control-tower routines, and continuous improvement cycles.

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