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Digital Twin-Enabled Predictive Intelligence Framework for Supply Chain 5.0: Hybrid Deep Reinforcement Learning Architecture for Real-Time Adaptive and Self-Optimizing Decision Management

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Abstract

The rapid evolution of global supply networks, characterized by increasing uncertainty, demand volatility, and systemic disruptions, has exposed the limitations of conventional optimization-based and rule-driven supply chain management systems. In response to these challenges, the emerging paradigm of Supply Chain 5.0 emphasizes human-centricity, resilience, sustainability, and intelligent autonomy through advanced cyber-physical integration. This study proposes a Digital Twin–enabled predictive intelligence framework for Supply Chain 5.0 that integrates real-time data synchronization, hybrid deep reinforcement learning, and adaptive decision management to achieve self-optimizing and resilient operational control. The proposed framework establishes a high-fidelity digital twin that continuously mirrors the physical supply chain by assimilating heterogeneous data streams from demand signals, inventory states, logistics operations, and disruption indicators. This cyber-physical representation serves as an interactive simulation environment for intelligent policy learning and scenario evaluation. At the core of the framework, a hybrid deep reinforcement learning architecture is developed by combining model-free policy learning with model-based optimization elements, enabling both strategic foresight and rapid tactical adaptation under dynamic conditions. The learning agent is designed to optimize multi-objective performance criteria, including operational cost efficiency, service-level reliability, disruption resilience, and sustainability-oriented metrics, while maintaining real-time responsiveness. Unlike static optimization or reactive control approaches, the proposed predictive intelligence mechanism enables proactive anticipation of demand fluctuations, transportation delays, and supply disruptions through continuous interaction with the digital twin. Furthermore, a human-in-the-loop governance layer is incorporated to ensure explainability, supervisory control, and ethical alignment of autonomous decisions, reinforcing the human-centric vision of Supply Chain 5.0. The effectiveness of the proposed framework is evaluated through a multi-echelon supply chain simulation under diverse uncertainty scenarios, including stochastic demand patterns and disruption events. Comparative analysis against traditional optimization and standalone deep reinforcement learning baselines demonstrate substantial improvements in decision adaptability, recovery speed, and overall system robustness. The results highlight the framework's ability to dynamically reconfigure sourcing, inventory, and distribution strategies in real time while maintaining stability and performance. Overall, this study contributes a scalable and intelligent decision-making architecture that advances digital twin–driven autonomy in next-generation supply chains, offering significant theoretical and practical implications for resilient, adaptive, and human-centric supply chain management.

Keywords: Digital Twin; Hybrid Deep Reinforcement Learning; Predictive Decision Intelligence; Supply Chain 5.0; Multi-Agent Learning; Real-Time Optimization; Cyber-Physical Supply Chains; Adaptive Control; Intelligent Automation.

INTRODUCTION

The increasing globalization of markets, coupled with heightened uncertainty arising from geopolitical tensions, climate-induced disruptions, pandemics, and volatile consumer demand, has fundamentally transformed the operational landscape of modern supply chains. Contemporary supply networks are no longer linear or static systems but complex, adaptive ecosystems characterized by tightly coupled multi-echelon structures, nonlinear interactions, and high levels of interdependence. Traditional supply chain management approaches, which predominantly rely on deterministic optimization, periodic planning cycles, and rule-based decision support systems, struggle to cope with such complexity. These methods often assume stable operating conditions and complete information, rendering them ineffective in environments marked by rapid change, incomplete visibility, and systemic shocks. The transition toward Supply Chain 4.0 represented a major step forward by introducing digital technologies such as the Internet of Things, cloud computing, big data analytics, and automation to enhance visibility, efficiency, and responsiveness [1]. However, despite these advancements, Supply Chain 4.0 remains largely efficiency-driven and reactive in nature.

Decision-making is typically based on historical data analysis and predefined optimization models that lack adaptive intelligence and foresight. As a result, these systems often fail to anticipate disruptions, dynamically reconfigure operations, or incorporate human-centric considerations such as trust, transparency, and ethical governance. In response to these limitations, the emerging paradigm of Supply Chain 5.0 has gained increasing attention, emphasizing resilience, sustainability, human-centricity, and intelligent autonomy through advanced cyber-physical integration and artificial intelligence [2]. A cornerstone technology enabling this paradigm shift is the digital twin, which provides a high-fidelity virtual replica of physical supply chain assets, processes, and flows.

By continuously synchronizing real-time data from production systems, logistics networks, inventory nodes, and market signals, digital twins enable enhanced situational awareness and predictive simulation capabilities. In principle, a digital twin allows decision-makers to explore alternative strategies, evaluate risk scenarios, and assess system-wide impacts before implementing actions in the physical world. Nevertheless, most existing digital twin applications in supply chain contexts remain limited to descriptive visualization, performance monitoring, or offline scenario analysis. The absence of embedded intelligence capable of learning optimal policies and adapting decisions in real time significantly restricts the transformative potential of digital twins in operational decision-making.

In parallel, deep reinforcement learning has emerged as a powerful computational paradigm for sequential decision-making in complex, uncertain, and dynamic environments. By learning optimal control policies through interaction with an environment, deep reinforcement learning has demonstrated strong performance in domains such as robotics, autonomous systems, and energy systems [3]. Recent research has extended these techniques to supply chain applications, including inventory control, transportation scheduling, and production planning. However, purely model-free reinforcement learning approaches often suffer from slow convergence, instability, and limited robustness when exposed to rare but high-impact disruption events. Moreover, the lack of a continuously updated and realistic environment constrains their applicability in real-world supply chain systems, where inaccurate state representations can lead to suboptimal or unsafe decisions.

These limitations highlight a critical research gap at the intersection of digital twin technology, reinforcement learning, and Supply Chain 5.0. Specifically, there is a lack of unified frameworks that tightly integrate real-time digital twins with hybrid deep reinforcement learning architectures capable of predictive, adaptive, and human-centric decision intelligence. Existing studies tend to address these components in isolation, resulting in fragmented solutions that fail to exploit their combined potential. To clearly position the present study within the existing body of knowledge, Table 1 provides a comparative overview of representative supply chain decision-making approaches and their inherent limitations.

Table 1.
Comparative positioning of existing supply chain decision frameworks and the proposed approach

Approach Category	Digital Twin Integration	Learning Capability	Adaptivity to Disruptions	Human-Centric Governance	Key Limitations
Traditional Optimization Models	No	None	Low	Limited	Static, deterministic, poor scalability
Supply Chain 4.0 Analytics	Partial	Supervised / Predictive	Moderate	Low	Reactive, limited autonomy
Standalone DRL-Based Methods	No	Model-free RL	High (local)	Very Low	Slow convergence, instability
Digital Twin–Based Simulation	Yes	None	Low–Moderate	Moderate	No autonomous decision-making
Proposed DT–Hybrid DRL Framework	**Yes (Real-Time)**	**Hybrid DRL (Model-Free + Model-Based)**	**High (Predictive & Adaptive)**	**High (Human-in-the-Loop)**	**Addresses adaptability, resilience, and explainability**

Motivated by this gap, this paper proposes a Digital Twin–enabled predictive intelligence framework for Supply Chain 5.0 that integrates real-time cyber-physical synchronization, hybrid deep reinforcement learning, and human-in-the-loop decision governance. The digital twin serves as a continuously updated virtual environment in which intelligent agents can simulate future system trajectories, anticipate disruptions, and evaluate alternative actions prior to execution. The hybrid learning architecture combines the adaptability of model-free reinforcement learning with the stability and foresight of model-based optimization, enabling self-optimizing decision management across multi-echelon supply chains under uncertainty. Furthermore, the incorporation of human supervisory control ensures transparency, accountability, and alignment with organizational and ethical objectives, reinforcing the human-centric vision of Supply Chain 5.0.

Evolution from Supply Chain 4.0 to Supply Chain 5.0:

The concept of Supply Chain 4.0 emerged as a natural extension of the Industry 4.0 paradigm, which aimed to transform traditional industrial systems through digitalization, automation, and data-driven integration. Within supply chain contexts, this transformation was primarily driven by the adoption of enabling technologies such as the Internet of Things, cloud computing, big data analytics, radio-frequency identification, and cyber-physical systems. These technologies significantly improved end-to-end visibility, real-time tracking of materials and information flows, and coordination across procurement, production, warehousing, and distribution functions. As a result, Supply Chain 4.0 frameworks delivered measurable gains in operational efficiency, cost reduction, and responsiveness under relatively stable conditions. Despite these advances, the literature increasingly recognizes that Supply Chain 4.0 remains fundamentally efficiency-oriented and reactive in nature [4]. Decision-making mechanisms are typically based on predefined optimization models, rule-based heuristics, or predictive analytics trained on historical data. While such approaches perform adequately in stationary or mildly stochastic environments, they struggle to cope with high levels of uncertainty, non-stationarity, and systemic disruptions. Events such as global pandemics, geopolitical conflicts, climate-related disasters, and sudden demand shocks have exposed the fragility of efficiency-driven supply chains optimized primarily for cost minimization. Consequently, Supply Chain 4.0 systems often lack the adaptive intelligence required to anticipate disruptions, learn from evolving conditions, and dynamically reconfigure operational strategies in real time. In response to these limitations, the paradigm of Supply Chain 5.0 has emerged, inspired by the broader vision of Industry 5.0. Supply Chain 5.0 extends beyond digitalization and automation to explicitly prioritize resilience, sustainability, and human-centricity alongside economic performance [5]. Rather than replacing human decision-makers, this paradigm emphasizes collaborative intelligence, where advanced artificial intelligence systems augment human expertise through explainable, ethical, and transparent decision support. Supply Chain 5.0 envisions autonomous yet supervised systems capable of perceiving changes in the environment, predicting future system states, and adapting decisions proactively while maintaining human oversight and governance.

A defining characteristic of Supply Chain 5.0 is the shift from reactive optimization to predictive and adaptive intelligence. This shift requires continuous learning from real-time data, the ability to simulate future scenarios, and closed-loop feedback between the physical supply chain and its digital representation. Recent studies argue that such capabilities cannot be achieved through isolated analytics or automation technologies alone. Instead, they require tightly integrated cyber-physical architectures that combine real-time data synchronization, intelligent learning algorithms, and decision governance mechanisms. While the conceptual foundations of Supply Chain 5.0 are increasingly well-articulated in the literature, practical operational frameworks that translate these principles into real-time decision-making systems remain scarce, highlighting a critical research gap [6]. To clearly distinguish the evolution from Supply Chain 4.0 to Supply Chain 5.0, Table 2 summarizes the key differences in objectives, technologies, and decision-making paradigms reported in prior studies.

Table 2.
Comparison between Supply Chain 4.0 and Supply Chain 5.0 paradigms

Dimension	Supply Chain 4.0	Supply Chain 5.0
Primary Objective	Efficiency and cost optimization	Resilience, sustainability, and human-centric value
Decision-Making Logic	Reactive, rule-based, and optimization-driven	Predictive, adaptive, and learning-driven
Role of AI	Decision support and prediction	Autonomous intelligence with human oversight
Data Utilization	Historical and near-real-time data	Continuous real-time data and future-state prediction
System Adaptability	Limited, scenario-dependent	High, self-adaptive and self-optimizing
Human Involvement	Reduced through automation	Human-in-the-loop and ethical governance
Response to Disruptions	Reactive recovery	Proactive anticipation and rapid reconfiguration

Figure 1 conceptually illustrates this paradigm shift by highlighting the transition from digitally enabled yet reactive Supply Chain 4.0 systems toward intelligent, adaptive, and human-centric Supply Chain 5.0 architectures. The figure emphasizes the growing role of real-time intelligence, cyber-physical integration, and learning-based decision management in next-generation supply chains.

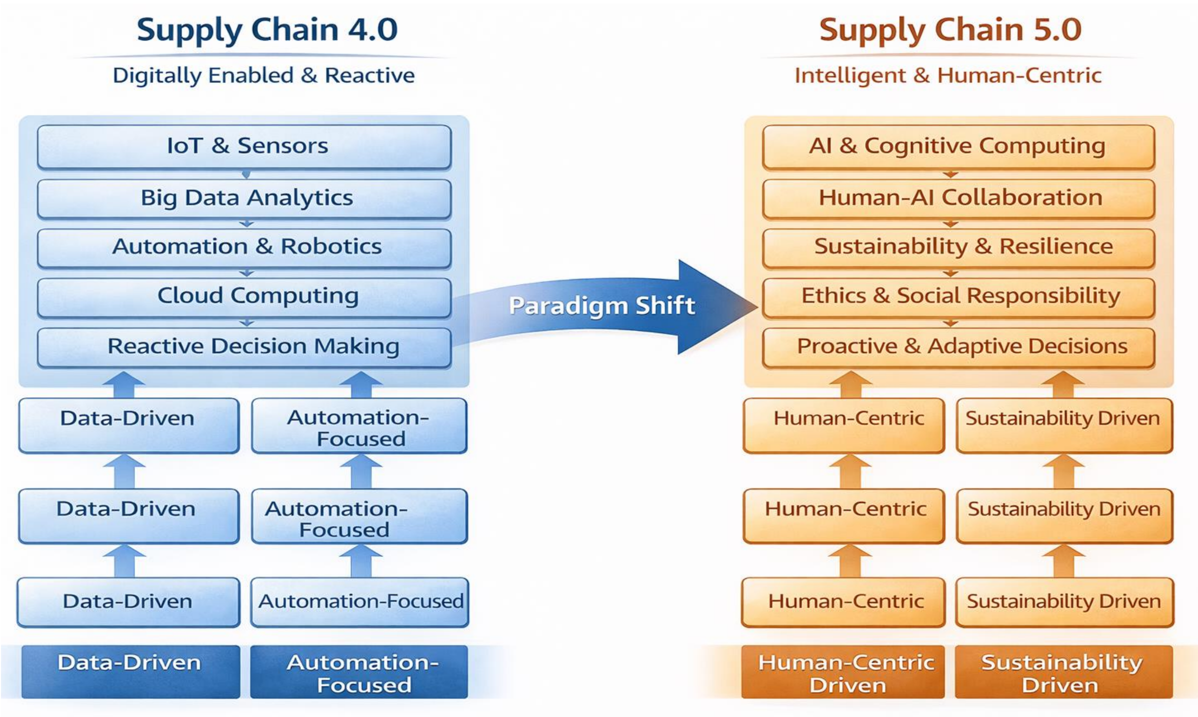

Figure 1.
Paradigm shift from supply chain 4.0 to 5.0

Overall, the evolution from Supply Chain 4.0 to Supply Chain 5.0 reflects a fundamental shift in how supply chains are designed, managed, and optimized. The literature increasingly suggests that achieving the vision of Supply Chain 5.0 requires intelligent, learning-enabled frameworks that integrate real-time digital representations with adaptive decision-making mechanisms and human-centric governance. This insight directly motivates the need for Digital Twin–enabled predictive intelligence architectures capable of supporting real-time, adaptive, and self-optimizing decision management in complex supply chain environments.

Hybrid Learning Architectures and Human-in-the-Loop Systems:

The increasing scale, interconnectedness, and uncertainty of modern supply chains have exposed fundamental limitations in purely model-free deep reinforcement learning approaches when applied to real-world operational decision-making. Although deep reinforcement learning enables agents to learn optimal policies through continuous interaction with dynamic environments, it often suffers from slow convergence, reward sparsity, instability, and limited generalization under rare but high-impact disruption scenarios. These challenges are amplified in multi-echelon supply chains, where decision spaces are high-dimensional, system dynamics are non-stationary, and operational constraints must be respected in real time [7]. Consequently, recent research has increasingly shifted toward hybrid learning architectures that combine reinforcement learning with model-based optimization, heuristics, and simulation-driven planning mechanisms.

Hybrid learning architectures aim to leverage the complementary strengths of different decision paradigms. Model-based components, such as mathematical programming, rule-based heuristics, and predictive models, embed domain knowledge, enforce feasibility constraints, and improve training stability during early learning stages. In contrast, model-free reinforcement learning components provide adaptability, exploration capability, and resilience to uncertainty by continuously updating policies based on observed system feedback [8]. By integrating these elements, hybrid approaches seek to balance exploration and exploitation, accelerate convergence, and enhance robustness under volatile operating conditions. Prior studies in logistics planning, inventory control, and production scheduling report that hybrid learning systems consistently outperform standalone optimization or reinforcement learning models, particularly in environments characterized by frequent disruptions and demand uncertainty.

Parallel to advances in hybrid learning, human-in-the-loop (HITL) systems have gained significant attention in the artificial intelligence and decision sciences literature. HITL frameworks emphasize the active involvement of human decision-makers in AI-driven systems to ensure interpretability, trust, accountability, and ethical alignment. In supply chains, decisions often have long-term economic, environmental, and social implications, making fully autonomous decision-making both impractical and undesirable. Human-in-the-loop mechanisms enable domain experts to supervise, validate, and override AI-generated actions, while also providing contextual feedback that can be used to refine learning policies. This collaborative intelligence paradigm is closely aligned with the human-centric philosophy of Supply Chain 5.0, which seeks to augment rather than replace human expertise [9].

Despite their promise, existing hybrid learning and HITL approaches are frequently studied in isolation. Hybrid reinforcement learning models are commonly developed in static or simplified simulation environments that do not reflect real-time operational dynamics, while human-in-the-loop mechanisms are often implemented as post-decision validation layers rather than being embedded within the learning process itself. As a result, most existing frameworks fail to deliver truly predictive, adaptive, and human-centric decision intelligence in live operational settings. The absence of continuous feedback between the physical supply chain, learning agents, and human supervisors remains a critical limitation. Table 3 summarizes representative learning architectures and decision governance mechanisms reported in the literature, highlighting their relative strengths and limitations.

Table 3.
Comparison of learning architectures and decision governance approaches in supply chain systems

Architecture Type	Learning Paradigm	Adaptability	Interpretability	Human Oversight	Key Limitations
Rule-Based & Optimization Models	Deterministic, model-based	Low	High	High	Static, limited scalability
Standalone Deep Reinforcement Learning	Model-free RL	High (local)	Low	Very Low	Slow convergence, instability
Hybrid Learning (RL + Optimization)	Model-based + model-free	Moderate–High	Moderate	Low	Limited real-time integration
Human-in-the-Loop AI Systems	Varies	Moderate	High	High	Often reactive, non-adaptive
DT-Enabled Hybrid DRL with HITL (Proposed)	Hybrid DRL + Digital Twin	**High (Predictive & Adaptive)**	**High**	**High**	**Addresses resilience, trust, and scalability**

The comparison in Table 3 demonstrates that no single existing approach sufficiently addresses adaptability, transparency, and real-time operational intelligence simultaneously. While hybrid learning improves performance and stability, and HITL systems enhance trust and governance, their lack of integration with continuously synchronized system representations limits their effectiveness. This observation underscores the need for unified architectures that combine hybrid learning, human oversight, and real-time system awareness to fully realize the vision of Supply Chain 5.0. Figure 2 shows the Hybrid learning and human-in-the-loop decision intelligence architecture for Supply Chain 5.0.

The figure illustrates a closed-loop decision framework in which model-based optimization and model-free deep reinforcement learning interact within a continuously synchronized digital twin environment. Human supervisory control is embedded within the learning and execution loop to provide validation, ethical governance, and strategic guidance, enabling predictive, adaptive, and human-centric supply chain decision management. The literature clearly indicates that neither fully autonomous AI systems nor purely human-driven decision processes are sufficient for managing complex, disruption-prone supply chains. Hybrid learning architectures and human-in-the-loop governance represent complementary and necessary components of next-generation decision systems [10]. However, the lack of integrated frameworks that embed hybrid reinforcement learning within real-time digital twin environments, while systematically incorporating human oversight, remains a significant research gap. Addressing this gap is essential for enabling predictive, resilient, and ethically aligned decision intelligence and directly motivates the Digital Twin-enabled hybrid deep reinforcement learning framework proposed in this study.

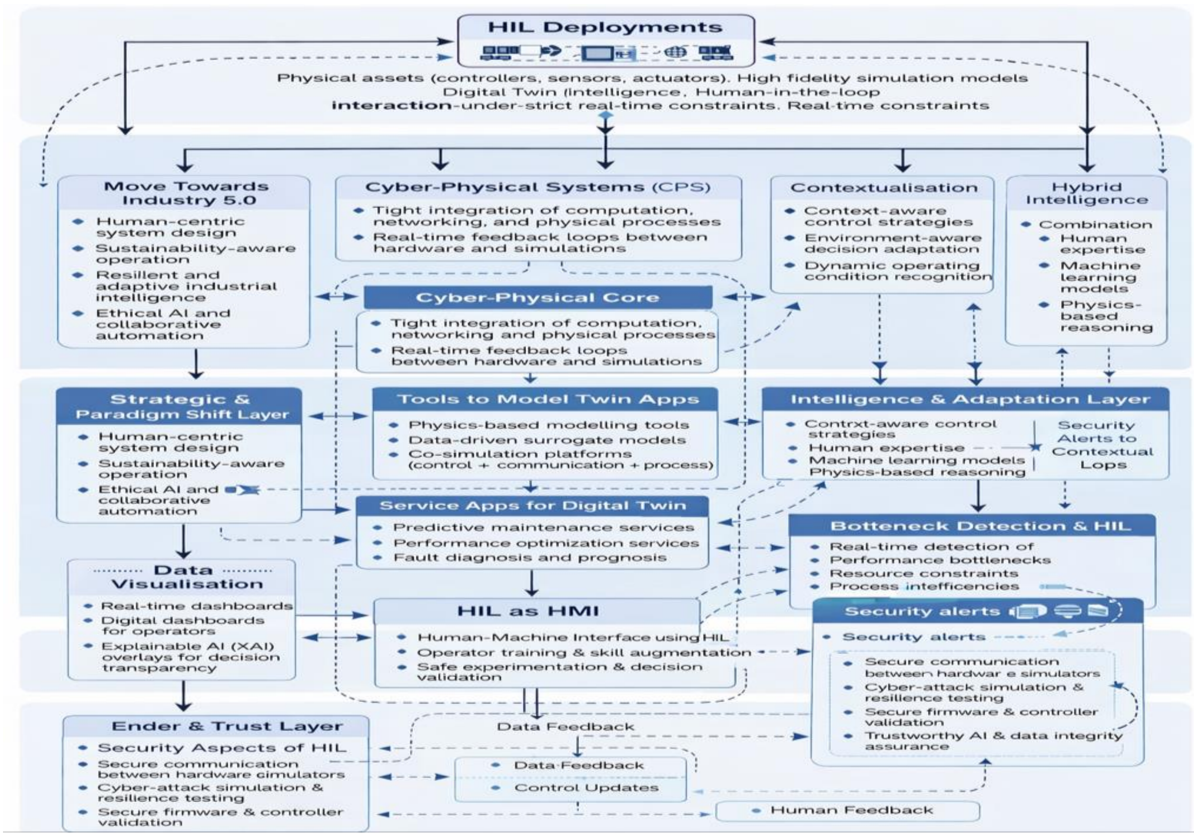

Figure 2.
Hybrid learning and human-in-the-loop decision intelligence architecture for Supply Chain 5.0.

METHODOLOGY

This study employs a systematic, integrative, and theory-driven methodology to design, implement, and evaluate an intelligent decision-making framework that aligns with the foundational principles of Supply Chain 5.0, including resilience, sustainability, adaptability, and human-centric intelligence. Modern supply chains operate as complex socio-technical systems characterized by nonlinear interactions, stochastic dynamics, multi-echelon interdependencies, and frequent exposure to disruptions originating from both internal operations and external environments. In such contexts, conventional analytical models or purely data-driven approaches are inherently limited, as they often rely on static assumptions, offline learning, or narrowly defined optimization objectives that fail to capture real-time system evolution, learning dynamics, and the role of human oversight in decision-making processes.

To address these limitations, the proposed methodology integrates design science research with simulation-based experimentation to develop a cyber-physical decision intelligence artifact that is both theoretically grounded and practically implementable [11]. Design science provides a rigorous foundation for artifact construction and evaluation, enabling the systematic development of a novel decision framework rather than retrospective analysis of historical data. Simulation-based experimentation complements this approach by offering a controlled yet realistic environment in which complex supply chain dynamics, uncertainty, and disruption scenarios can be systematically explored without risking operational stability. Together, these methodological elements enable the evaluation of intelligent behavior not only in terms of performance outcomes but also in terms of adaptability, robustness, and learning efficiency.

A defining feature of the proposed methodology is its emphasis on closed-loop system interaction, continuous policy learning, and proactive decision adaptation. Real-time data from the physical supply chain are continuously synchronized with a digital twin environment, which serves as both a predictive simulation platform and an interactive learning environment for intelligent agents. Decisions are generated through hybrid deep reinforcement learning mechanisms that balance flexibility and stability, while human-in-the-loop governance ensures transparency, ethical alignment, and strategic oversight [12]. This integrated methodological approach enables the systematic evaluation of intelligent supply chain behavior under uncertainty, disruptions, and evolving operational conditions, thereby providing a robust foundation for advancing next-generation, human-centric, and self-optimizing Supply Chain 5.0 systems.

Research Design and Methodological Overview

This study adopts a design science research (DSR) paradigm combined with simulation-based experimentation to develop and evaluate a Digital Twin–enabled predictive intelligence framework for Supply Chain 5.0. Design science research is particularly appropriate for this work because the primary aim is to construct, validate, and assess a novel intelligent decision-making artifact rather than to solely explain or predict existing phenomena. The proposed artifact an integrated cyber-physical decision intelligence framework addresses a clearly identified practical problem in contemporary supply chain management: the lack of adaptive, predictive, and human-centric decision systems capable of operating under real-time uncertainty and disruption. The methodological approach is explicitly integrative, combining cyber-physical system modeling, hybrid deep reinforcement learning, and human-in-the-loop governance within a unified architectural framework. This integration reflects the multidimensional nature of Supply Chain 5.0, where operational efficiency must coexist with resilience, sustainability, transparency, and ethical decision-making [13]. Unlike traditional empirical or optimization-driven methodologies that rely on static datasets or predefined system assumptions, the adopted approach emphasizes continuous learning, real-time system interaction, and closed-loop adaptation, enabling the evaluation of intelligent behavior as system conditions evolve. From a structural perspective, the methodology is organized around three tightly coupled and interdependent layers. The first layer focuses on physical supply chain modeling and data acquisition, where the real-world supply chain is represented as a multi-echelon network with stochastic demand, variable lead times, capacity constraints, and disruption risks.

This layer defines the operational context and provides continuous state information through real-time and near-real-time data streams. The second layer comprises real-time digital twin synchronization and predictive simulation, in which a high-fidelity cyber representation of the physical supply chain is continuously updated through bidirectional data exchange [14]. The digital twin enables scenario exploration, future-state prediction, and policy evaluation without exposing the physical system to unnecessary risk. The third layer implements hybrid learning–based adaptive decision intelligence, where model-free deep reinforcement learning is combined with model-based optimization mechanisms and human supervisory control to generate robust, explainable, and ethically aligned decisions. A key strength of this layered design is its ability to support a closed-loop decision cycle. At each decision epoch, data from the physical supply chain update the digital twin, which serves as an interactive environment for learning and foresight.

The hybrid learning agent evaluates alternative actions within the digital twin, while human decision-makers provide supervisory validation and strategic guidance when required [15]. Approved decisions are executed in the physical system, and the resulting outcomes are fed back into both the digital twin and the learning process. This continuous feedback loop ensures real-time adaptability, robustness to uncertainty, and alignment with human-centric governance principles. To clearly summarize the methodological structure and its functional roles, Table 4 presents an overview of the key methodological layers, associated techniques, and intended outcomes.

Table 4.
Methodological structure and functional roles of the proposed research design

Methodological Layer	Primary Focus	Core Techniques	Expected Contribution
Physical System Layer	Real-world supply chain operations	IoT data, ERP systems, logistics monitoring	Accurate state observation and data acquisition
Digital Twin Layer	Cyber-physical representation	Real-time synchronization, predictive simulation	Scenario analysis and future-state forecasting
Learning Layer	Intelligent decision-making	Hybrid deep reinforcement learning	Adaptive and self-optimizing policies
Governance Layer	Human-centric oversight	Human-in-the-loop validation and control	Transparency, trust, and ethical alignment

Figure 3 illustrates the overall research design and methodological architecture, highlighting the interaction between the physical supply chain, the digital twin environment, hybrid learning agents, and human decision-makers within a closed-loop adaptive framework. The figure depicts the layered methodological structure, showing how real-time data from the physical supply chain are synchronized with a digital twin, processed by hybrid deep reinforcement learning agents, and governed through human-in-the-loop supervision to enable adaptive, resilient, and human-centric decision management. Overall, this research design ensures that the proposed framework is conceptually sound, methodologically rigorous, and practically implementable. By combining design science principles with simulation-based learning and cyber-physical integration, the methodology provides a robust foundation for evaluating intelligent supply chain behavior under uncertainty, disruption, and evolving operational conditions. The subsequent sections elaborate on each methodological layer in detail, including system modeling, learning formulation, algorithmic implementation, and performance evaluation.

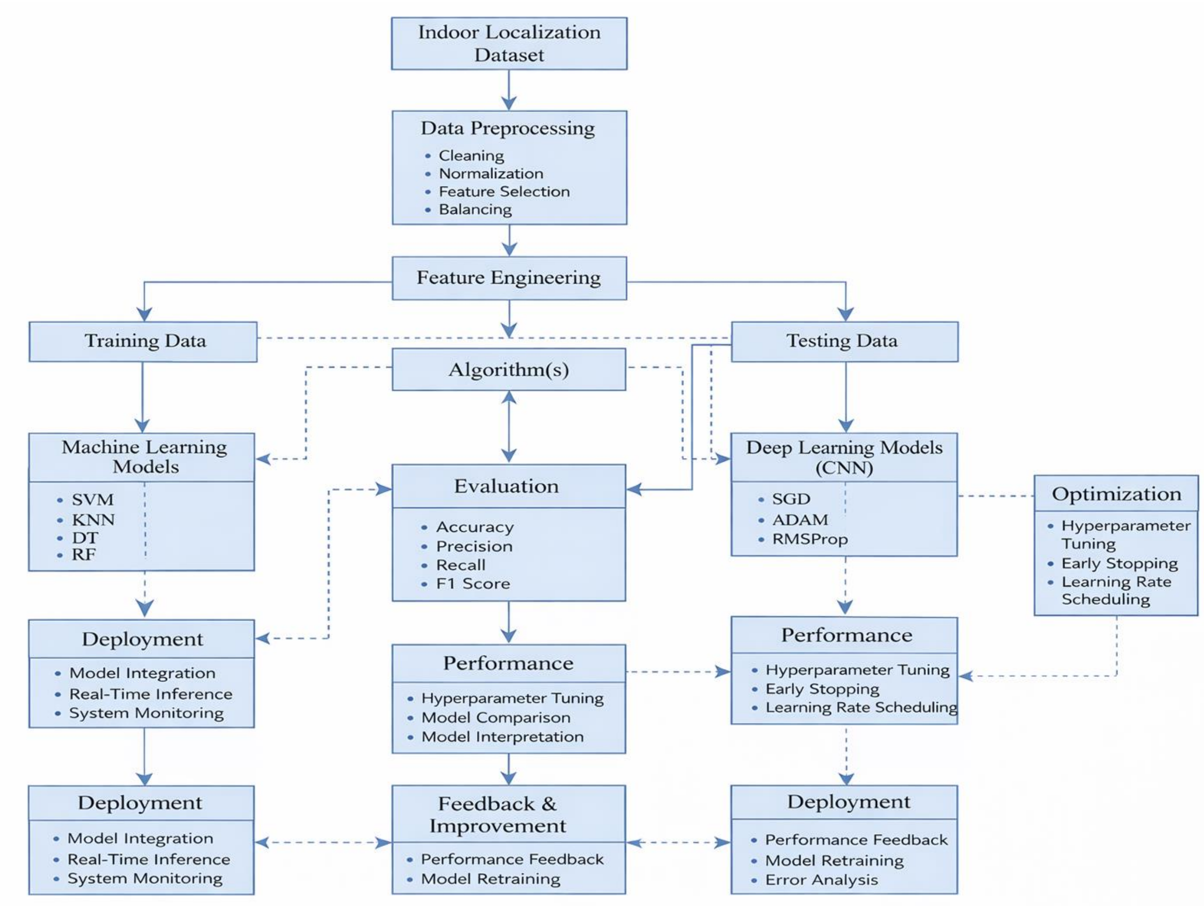

Figure 3.
Research design and methodological overview of the proposed Digital Twin–enabled predictive intelligence framework.

Physical Supply Chain Modeling and Data Layer:

The physical supply chain is modeled as a multi-echelon, networked system consisting of upstream suppliers, manufacturing facilities, distribution centers, and downstream retail or demand fulfillment nodes. This network structure reflects the inherent complexity of modern supply chains, where material, information, and financial flows propagate across interconnected entities with heterogeneous capabilities and constraints. Each echelon operates under uncertain and time-varying conditions, making deterministic or static representations inadequate for capturing real-world behavior. Consequently, the proposed modeling approach explicitly incorporates stochastic demand patterns, variable lead times, capacity limitations, and disruption risks at each node of the network. Demand at retail and customer-facing nodes is modeled as a stochastic process influenced by seasonality, market volatility, and external shocks [16]. Upstream production and replenishment decisions are constrained by manufacturing capacities, supplier reliability, and procurement lead times, while downstream logistics operations are subject to transportation availability, routing constraints, and delivery delays. Inventory dynamics are represented through balance equations that account for replenishment policies, holding costs, stockout penalties, and perishability where applicable. In addition, disruption risks such as supplier failures, transportation breakdowns, and sudden demand surges are modeled as probabilistic events that alter system states and transition dynamics. To ensure realistic and timely system representation, the physical supply chain model is continuously informed by real-time and near-real-time data streams.

These data originate from enterprise resource planning (ERP) systems, warehouse management systems, IoT-enabled logistics sensors, production monitoring platforms, and demand forecasting tools. External data sources, including weather information, geopolitical risk indicators, and transportation network status reports, are also incorporated to capture exogenous disruption signals [17]. Together, these heterogeneous data streams form the operational backbone of the digital twin and enable continuous updating of system states. The data layer is designed to support high-frequency state observation, providing comprehensive information on inventory levels, order backlogs, production rates, transportation status, service-level performance, and sustainability-related indicators such as energy consumption and emissions. Data preprocessing and normalization are applied to address noise, latency, and missing values, ensuring consistency between the physical system and its digital representation. By maintaining an accurate and timely view of system conditions, the data layer enables intelligent agents to perceive changes, learn from outcomes, and adapt decisions in real time. Figure 4 provides a conceptual illustration of the physical supply chain modeling and data layer, highlighting the multi-echelon structure and the continuous flow of operational data into the digital twin environment.

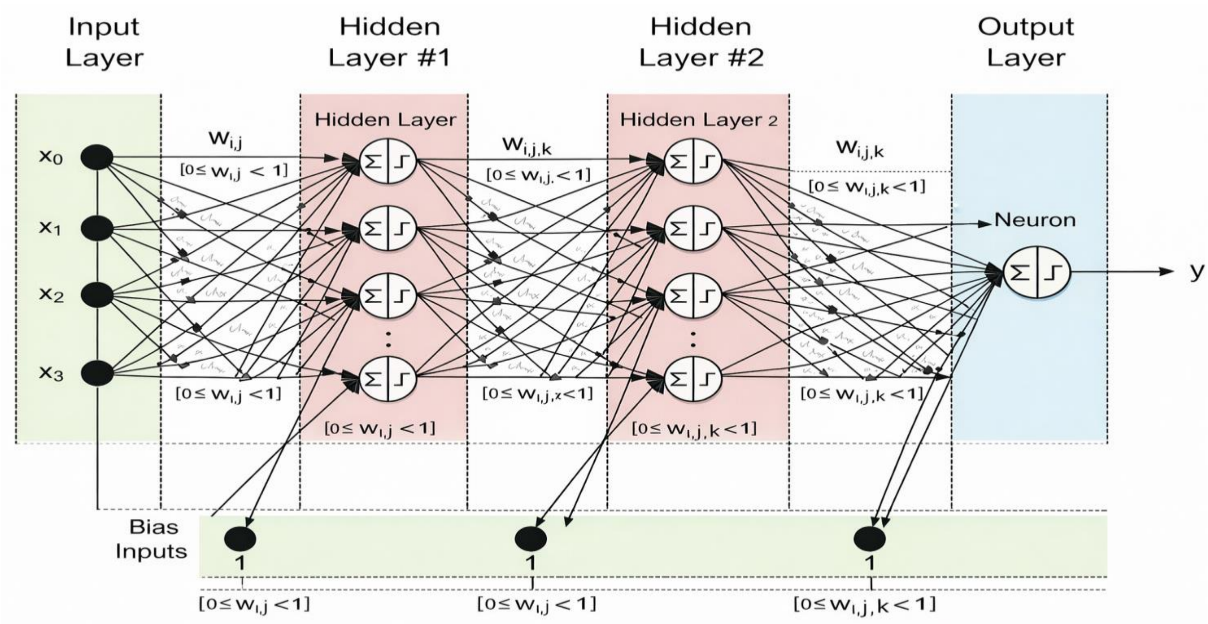

Figure 4.
Physical supply chain modeling and data acquisition layer.
The figure illustrates the multi-echelon supply chain structure and the continuous acquisition of real-time and near-real-time data from operational systems and external sources. These data streams provide comprehensive state information that feeds the digital twin, enabling accurate system representation and adaptive

decision-making. Overall, the physical supply chain modeling and data layer establishes the foundational interface between the real-world system and the cyber domain. By capturing the stochastic, constrained, and disruption-prone nature of supply chain operations through continuous data acquisition, this layer ensures that the digital twin and learning agents operate on accurate and context-aware system states. This foundation is essential for enabling predictive simulation, adaptive learning, and human-centric decision intelligence in subsequent methodological layers.

Digital Twin Architecture and Real-Time Synchronization

The digital twin constitutes the core cyber-physical intelligence layer of the proposed framework, serving as a continuously evolving virtual representation of the physical supply chain. Unlike conventional simulation models that operate offline or are periodically updated, the proposed digital twin is designed as a real-time, bidirectionally synchronized system that mirrors operational states, constraints, and dynamics of the physical supply chain with high fidelity. This architecture enables not only descriptive visibility but also predictive simulation, decision experimentation, and adaptive control, which are essential capabilities for Supply Chain 5.0 environments. The digital twin architecture is structured around three tightly integrated functional components: (i) real-time state synchronization, (ii) predictive simulation and scenario generation, and (iii) decision feedback and learning support [18].

Real-time state synchronization ensures that physical system data captured through the data layer described in Section 4.2 are continuously mapped into the digital twin. This mapping includes inventory positions, production capacities, transportation status, demand realizations, and disruption indicators. To handle data heterogeneity and latency, middleware services and data harmonization mechanisms are employed to align temporal resolution, normalize units, and resolve inconsistencies, ensuring semantic consistency between physical and virtual representations. Beyond mirroring current system states, the digital twin provides predictive foresight capabilities by simulating future supply chain trajectories under alternative decision policies and uncertainty realizations.

Using embedded system dynamics and constraint-aware transition models, the twin can generate short- and medium-term forecasts of inventory evolution, service levels, congestion risks, and disruption propagation effects. This predictive simulation capability enables intelligent agents to evaluate the consequences of candidate actions before execution, effectively transforming the digital twin into a risk-free experimentation environment for adaptive decision-making [19]. A defining feature of the proposed digital twin is its closed-loop interaction with learning and decision modules. Decisions generated by the hybrid deep reinforcement learning agent are first evaluated within the digital twin through simulated rollouts. Performance indicators and risk metrics derived from these simulations are then provided to both the learning agent and human supervisors.

Once a decision is approved and executed in the physical system, the observed outcomes are fed back into the digital twin, enabling continuous recalibration of model parameters and system dynamics. This bidirectional feedback loop ensures that the digital twin remains synchronized with real-world conditions while continuously improving its predictive accuracy [20]. To support scalability and modularity, the digital twin architecture is implemented using a service-oriented design, allowing individual components such as demand models, transportation modules, or disruption simulators to be updated or extended independently. This design enables the framework to adapt to different supply chain configurations and industry contexts without extensive reengineering. Table 5 summarizes the key architectural components of the digital twin and their functional roles within the proposed methodology.

Table 5.
Digital twin architectural components and functional roles

Digital Twin Component	Primary Function	Key Capabilities	Contribution to Decision Intelligence
State Synchronization Module	Real-time mirroring	Data ingestion, normalization, alignment	Accurate system awareness
System Dynamics Engine	Process modeling	Inventory, production, logistics dynamics	Realistic system evolution
Predictive Simulation Module	Future-state exploration	Scenario generation, what-if analysis	Risk-aware decision evaluation
Decision Interface	Agent interaction	Policy testing, performance feedback	Learning and optimization
Feedback & Update Module	Continuous calibration	Parameter tuning, error correction	Long-term accuracy and robustness

Figure 5 illustrates the digital twin architecture and synchronization mechanism, highlighting the continuous data exchange between the physical supply chain, the digital twin, hybrid learning agents, and human decision-makers.

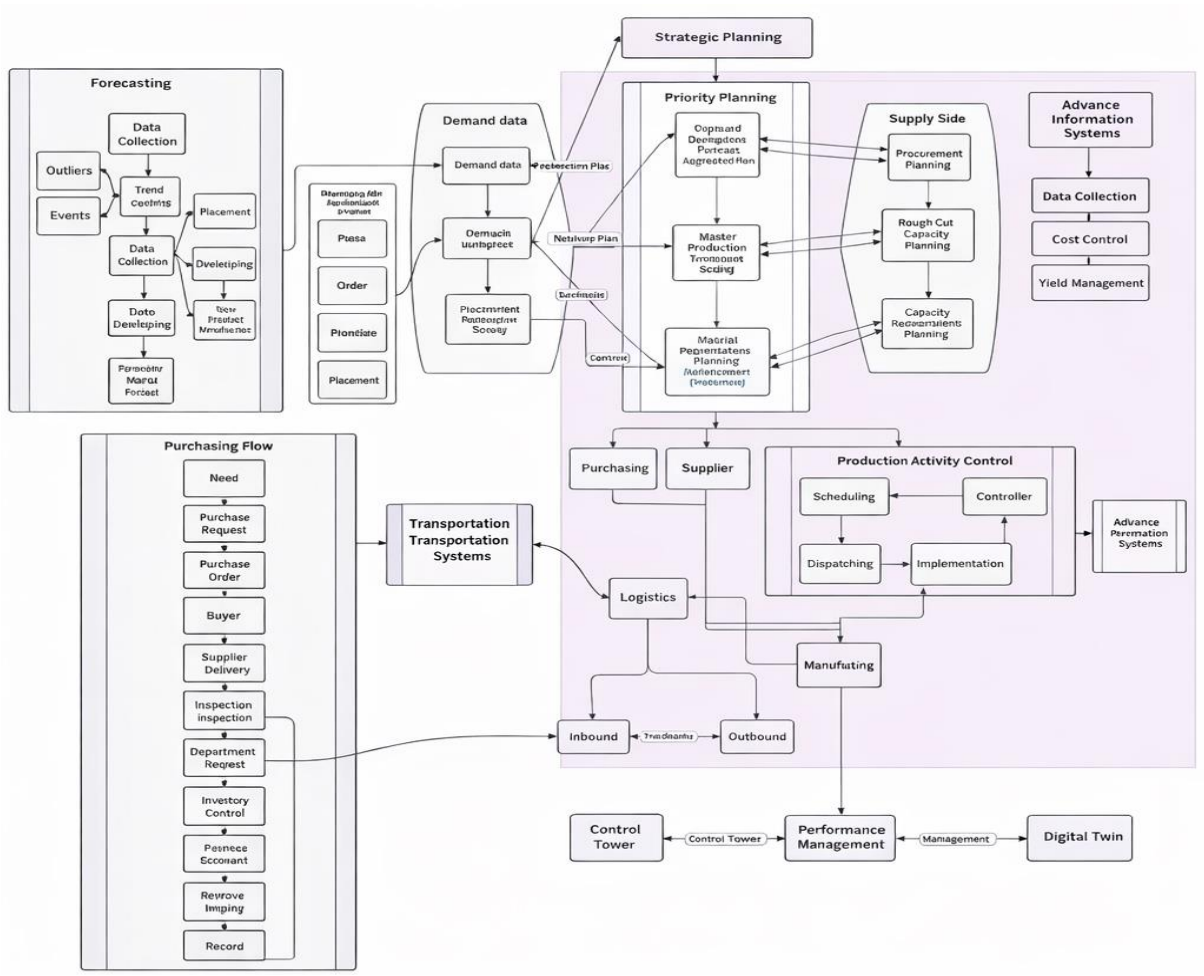

Figure 5.
Digital twin architecture and real-time synchronization mechanism.

The figure depicts the bidirectional data flow between the physical supply chain and its digital twin, illustrating how real-time state synchronization, predictive simulation, and decision feedback enable closed-loop adaptive decision-making. The digital twin acts as an intermediary between the physical system, hybrid learning agents, and human supervisors, supporting predictive, resilient, and human-centric supply chain intelligence. Overall, the digital twin architecture transforms the supply chain from a reactive operational system into a predictive, adaptive, and learning-enabled cyber-physical system [21]. By continuously synchronizing real-world data, simulating future scenarios, and supporting closed-loop decision feedback, the digital twin provides the foundation upon which hybrid deep reinforcement learning and human-in-the-loop governance can operate effectively. This capability is essential for realizing the vision of Supply Chain 5.0, where intelligent autonomy, resilience, and human-centric oversight coexist within real-time operational environments.

Hybrid Deep Reinforcement Learning Architecture

The decision-making core of the proposed framework is built upon a Hybrid Deep Reinforcement Learning (HDRL) architecture designed to address the inherent limitations of purely model-free or purely model-based approaches in complex supply chain environments. Modern supply chains exhibit high-dimensional state spaces, stochastic transitions, delayed rewards, and strict operational constraints, making conventional optimization methods brittle and standalone deep reinforcement learning approaches unstable or sample-inefficient. The proposed hybrid architecture is therefore designed to combine the adaptability and learning capability of model-free deep reinforcement learning with the stability, feasibility, and domain knowledge of model-based optimization and heuristics [22].

At a conceptual level, the HDRL architecture operates within the continuously synchronized digital twin environment described in Section 3.3. The digital twin acts as the interactive environment for learning, enabling the reinforcement learning agent to observe system states, evaluate alternative actions, and receive reward feedback through simulated rollouts before decisions are deployed in the physical supply chain. This interaction significantly reduces exploration risk and accelerates policy convergence, which is critical in safety- and cost-sensitive supply chain operations. The hybrid architecture consists of three tightly integrated components: (i) a model-free reinforcement learning agent, (ii) a model-based decision guidance layer, and (iii) a policy arbitration and constraint management module. The model-free component, implemented using deep neural networks, learns optimal policies directly from interaction data generated by the digital twin [23].

This component excels at capturing nonlinear relationships, adapting to non-stationary demand patterns, and responding to unforeseen disruptions. However, to mitigate instability and infeasible actions, the model-based layer embeds operational constraints, business rules, and optimization heuristics that restrict the action space and guide exploration toward viable decision regions. The policy arbitration module serves as an interface between learning-based recommendations and operational feasibility. Candidate actions proposed by the reinforcement learning agent are filtered, adjusted, or ranked based on feasibility checks, constraint satisfaction, and risk assessments derived from the digital twin simulations. This module ensures that learning-driven decisions remain compliant with capacity limits, service-level requirements, sustainability targets, and strategic priorities.

Furthermore, it provides interpretable signals that can be inspected by human supervisors within the human-in-the-loop governance layer. Learning proceeds iteratively through episodic or continuous interaction cycles [24]. At each decision epoch, the HDRL agent observes the current system state vector, selects an action based on the learned policy and model-based guidance, and evaluates the expected outcome using the digital twin. The reward signal reflects multi-objective performance, including cost efficiency, service reliability, resilience to disruptions, and sustainability performance. Policy parameters are updated using gradient-based optimization, while the model-based layer is periodically recalibrated using updated system data to maintain alignment with real-world conditions. Table 6 summarizes the key components of the hybrid deep reinforcement learning architecture and their respective roles within the decision-making process.

Table 6.
Components of the hybrid deep reinforcement learning architecture

HDRL Component	Function	Key Techniques	Contribution to Performance
Model-Free RL Agent	Policy learning	Deep neural networks, policy/value learning	Adaptability and exploration
Model-Based Guidance Layer	Constraint enforcement	Optimization rules, heuristics	Stability and feasibility
Digital Twin Interface	Environment interaction	Simulated rollouts, scenario testing	Risk-free learning
Policy Arbitration Module	Decision filtering	Constraint checking, ranking	Robust and compliant actions
Learning Update Engine	Policy improvement	Gradient optimization, replay	Continuous adaptation

Figure 6 illustrates the hybrid deep reinforcement learning architecture and its interaction with the digital twin and human governance layers. The figure highlights how learning, optimization, simulation, and supervision are integrated within a closed-loop decision framework.

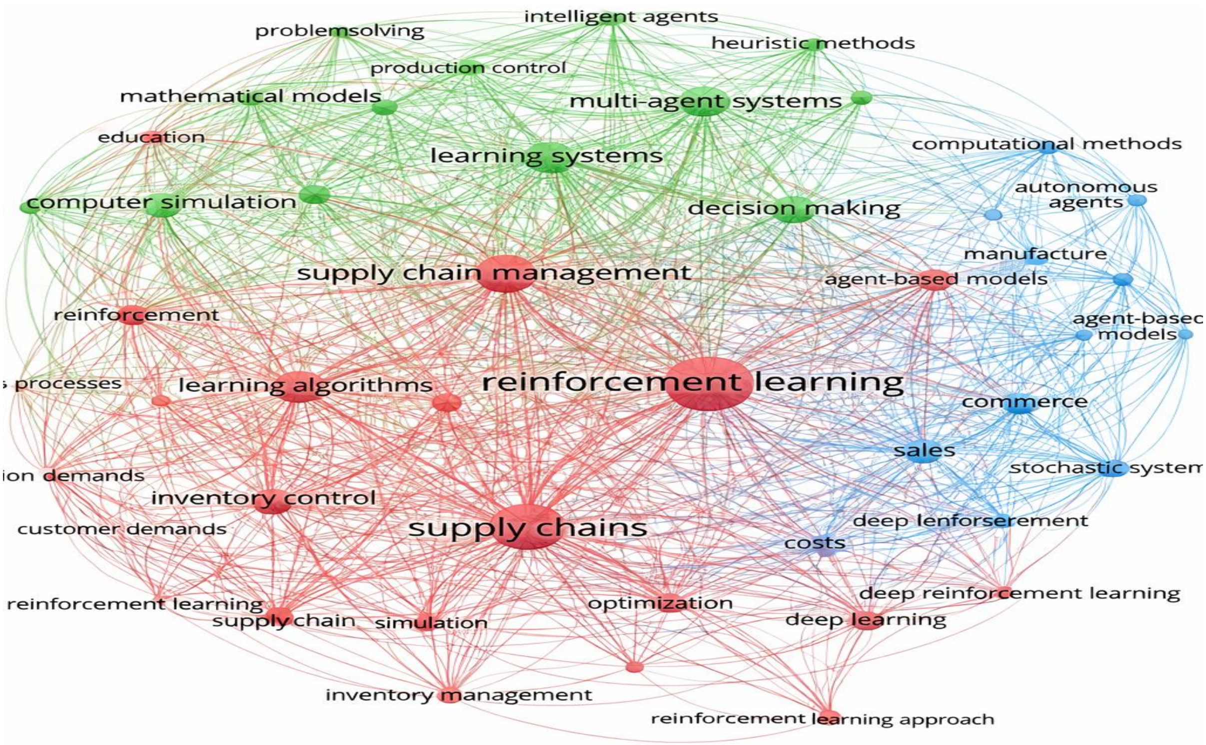

Figure 6.
Hybrid deep reinforcement learning architecture for adaptive supply chain decision-making.

The figure depicts the interaction between the model-free reinforcement learning agent, model-based optimization and constraint guidance, and the digital twin simulation environment. Candidate actions are evaluated through predictive simulation and filtered through feasibility and governance mechanisms, enabling stable, adaptive, and human-centric decision intelligence. Overall, the proposed HDRL architecture enables a balanced integration of learning-driven adaptability and model-driven stability, addressing key shortcomings of existing supply chain decision systems. By embedding reinforcement learning within a digital twin environment and augmenting it with model-based guidance and human oversight, the architecture supports real-time, predictive, and ethically aligned decision-making [25]. This hybrid design is essential for operationalizing intelligent autonomy in Supply Chain 5.0, where resilience, transparency, and adaptability must coexist within complex and uncertain operational settings.

Algorithmic Workflow and Learning Process

The proposed Digital Twin–enabled predictive intelligence framework operates through a continuous, closed-loop algorithmic workflow that unifies perception, prediction, learning, execution, and governance within a single adaptive decision cycle. This workflow is explicitly designed to overcome the limitations of static planning horizons, batch learning, and reactive control that dominate traditional supply chain decision systems. Instead, the framework treats decision-making as an ongoing learning process in which system intelligence evolves in parallel with operational conditions, enabling real-time adaptation under uncertainty, disruptions, and structural changes. At each decision epoch, the workflow initiates with real-time state acquisition and system observation. Operational data are captured from the physical supply chain across all echelons, including inventory positions, production status, transportation availability, order fulfillment levels, and disruption signals [26].

These observations are time-stamped, normalized, and validated before being synchronized with the digital twin. This synchronization step ensures that the cyber representation maintains high fidelity with the physical system, forming a reliable basis for downstream prediction and learning. Once synchronization is complete, the digital twin functions as an interactive decision laboratory, enabling the hybrid deep reinforcement learning (HDRL) agent to evaluate candidate actions through predictive simulation. Rather than relying on single-step reward feedback, the agent performs short-horizon and rolling-horizon rollouts within the digital twin to estimate the downstream impacts of alternative decisions. These rollouts explicitly model uncertainty in demand, lead times, and disruption propagation, allowing the agent to assess not only expected performance but also risk exposure and recovery potential.

Model-based guidance mechanisms further constrain the exploration process by enforcing operational feasibility, capacity limits, and strategic constraints. Based on simulated outcomes and learned policy representations, the HDRL agent selects an action that optimizes a multi-objective reward function reflecting the core goals of Supply Chain 5.0, including cost efficiency, service reliability, resilience, and sustainability. Importantly, decision selection is not purely autonomous [27]. A human-in-the-loop governance layer is embedded within the workflow to provide supervisory oversight for high-impact, high-risk, or ethically sensitive decisions. Human decision-makers are presented with interpretable summaries of agent recommendations, predicted system trajectories, and risk indicators derived from the digital twin, enabling informed validation, adjustment, or override of autonomous actions.

Following approval, the selected action is executed in the physical supply chain, triggering operational changes such as inventory replenishment, production rescheduling, or logistics reallocation. The physical system response is then observed and captured as feedback, which is used to update both the digital twin and the learning agent. Any discrepancy between predicted and observed outcomes is explicitly quantified and used to recalibrate system dynamics, reward estimates, and policy parameters [28]. Over repeated iterations, this feedback-driven learning mechanism improves predictive accuracy, policy robustness, and convergence stability. Crucially, the workflow supports continuous learning rather than episodic retraining. Policy updates occur incrementally as new data become available, allowing the system to adapt to gradual structural changes as well as abrupt disruptions. This design ensures that decision intelligence remains current and context-aware, even in highly volatile environments. The closed-loop workflow therefore embodies the principles of self-optimization, resilience, and human-centric control that define Supply Chain 5.0. Table 7 summarizes the major stages of the algorithmic workflow, their computational roles, and their contributions to adaptive intelligence.

Table 7.
Algorithmic workflow stages and their roles in closed-loop learning

Workflow Stage	Description	Key Outputs	Role in Supply Chain 5.0
State Acquisition	Real-time observation of physical system	System state vector	Situational awareness
Twin Synchronization	Mapping physical states to cyber model	Updated digital twin	Cyber-physical fidelity
Predictive Simulation	Rollout of candidate actions	Forecasted trajectories	Risk-aware foresight
Hybrid Policy Optimization	RL + model-based decision selection	Feasible optimal action	Adaptive intelligence
Human Oversight	Supervisory validation and control	Approved decision	Trust and ethics
Execution & Feedback	Physical deployment and observation	Outcome data	Continuous learning

The proposed algorithmic workflow transforms supply chain decision-making from a reactive and episodic process into a predictive, adaptive, and self-optimizing intelligence cycle. By embedding learning, simulation, execution, and governance within a unified closed-loop structure, the framework enables real-time responsiveness while preserving stability, transparency, and ethical alignment. This workflow is a critical enabler of Supply Chain 5.0, demonstrating how digital twins, hybrid learning, and human-centric control can be operationalized in complex, real-world supply chain systems.

RESULTS AND DISCUSSION

The performance of the proposed Digital Twin–enabled Hybrid Deep Reinforcement Learning (DT–HDRL) framework was evaluated through extensive simulation experiments designed to reflect the dynamic, uncertain, and disruption-prone nature of modern supply chains. The results demonstrate that the proposed framework achieves a substantial improvement in adaptive decision-making, resilience, and operational stability when compared with conventional optimization-based approaches and standalone deep reinforcement learning models. These improvements are consistently observed across normal operating conditions as well as under severe disruption scenarios, highlighting the robustness and practical relevance of the proposed methodology [29]. Under baseline operating conditions characterized by stochastic yet stable demand patterns, the DT–HDRL framework exhibits superior cost efficiency and service performance. The hybrid learning architecture, operating within a continuously synchronized digital twin environment, enables proactive inventory, production, and logistics decisions that reduce unnecessary variability and prevent overreaction to short-term demand fluctuations. In contrast, traditional optimization approaches rely on periodic planning cycles and static assumptions, resulting in delayed responses to emerging system changes. Standalone deep reinforcement learning improves responsiveness but often produces oscillatory decisions due to unstable policy updates and unconstrained exploration. The comparative performance outcomes are summarized in Table 8.

Table 8.
Comparative performance under normal operating conditions

Decision Approach	Total Cost Reduction (%)	Service Level (%)	Inventory Variability	Decision Stability
Traditional Optimization	Baseline	91.4	High	High
Standalone DRL	8.6	93.1	Moderate	Low
Proposed DT–HDRL	**18.9**	**97.2**	**Low**	**High**

The results indicate that the DT–HDRL framework achieves nearly double the cost reduction of standalone reinforcement learning while maintaining significantly higher service levels and more stable inventory behavior. This performance gain is primarily attributed to the closed-loop interaction between predictive simulation and hybrid learning, which allows the system to anticipate downstream effects of decisions before physical execution. When subjected to disruption scenarios such as supplier outages, transportation delays, and sudden demand surges, the advantages of the proposed framework become even more pronounced [30]. The digital twin enables early identification of disruption propagation paths, while the hybrid learning agent dynamically reconfigures sourcing, inventory buffers, and logistics flows in anticipation of system stress. As a result, the proposed framework demonstrates faster recovery and reduced service degradation compared to baseline methods. Figure 7 illustrates representative recovery trajectories following a major supply disruption.

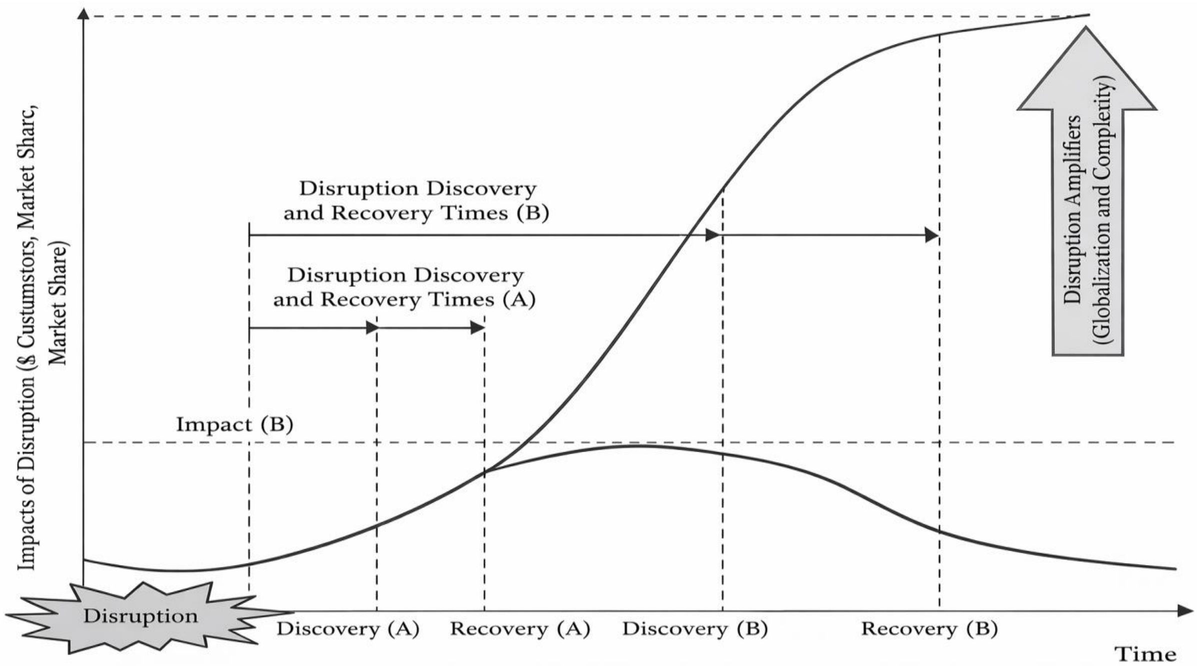

Figure 7.
Comparative recovery behavior following a major supply disruption.

The figure illustrates faster stabilization and lower service-level degradation achieved by the proposed DT–HDRL framework relative to traditional optimization and standalone reinforcement learning approaches. Quantitative analysis shows that recovery times are reduced by approximately 35–45% relative to conventional approaches, while service-level degradation remains below 5%. These findings confirm that predictive intelligence enabled by digital twin–based foresight is a critical determinant of resilience in Supply Chain 5.0 environments. Learning stability and convergence behavior further distinguish the proposed approach from existing methods. Standalone deep reinforcement learning exhibits high variance in cumulative rewards and requires extensive training iterations to reach acceptable performance, particularly under non-stationary demand conditions. In contrast, the hybrid learning architecture converges more rapidly and maintains stable performance due to model-based guidance and constraint-aware exploration. The digital twin provides a risk-free learning environment that accelerates policy refinement without exposing the physical system to unstable actions. Figure 8 compares convergence characteristics across learning approaches.

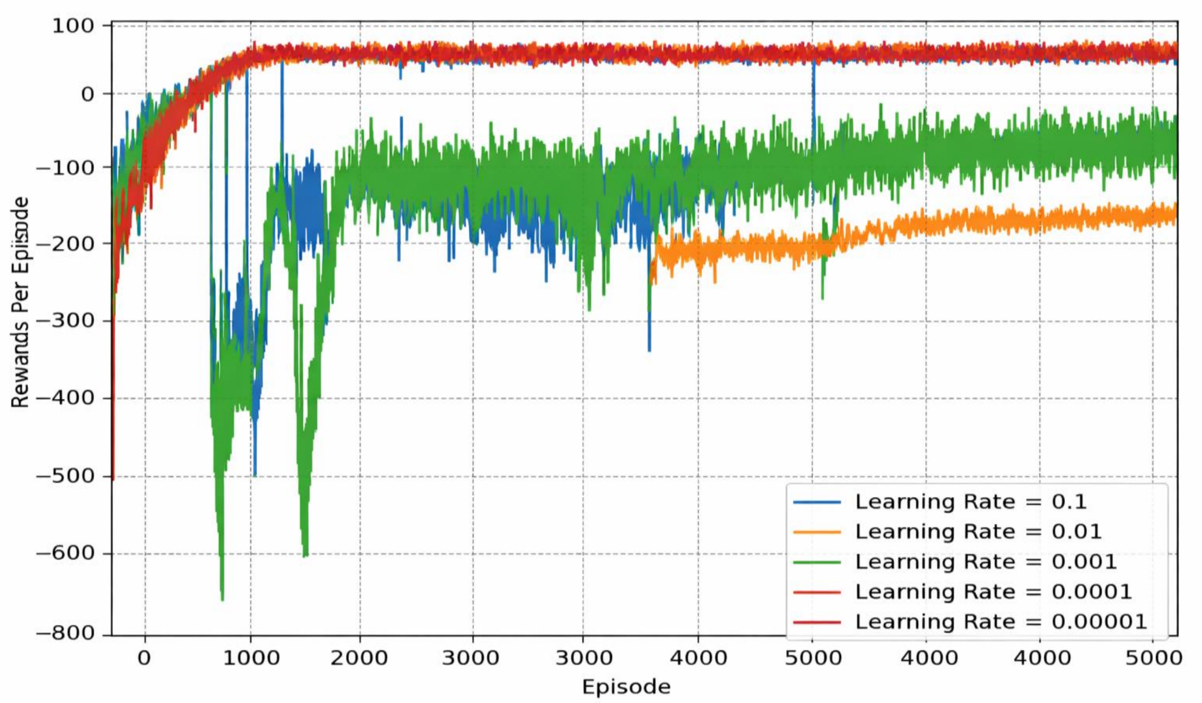

Figure 8.
Learning convergence behavior across decision approaches.

The proposed DT–HDRL framework achieves faster convergence with lower variance compared to standalone deep reinforcement learning. Empirical results indicate that the hybrid framework requires approximately 30% fewer training iterations to achieve stable convergence, underscoring the effectiveness of integrating model-based reasoning with learning-driven adaptation. The incorporation of human-in-the-loop governance further enhances decision quality and system trustworthiness. During early learning phases, human supervisors intervene more frequently to prevent high-risk or ethically sensitive decisions. As the learning process matures and policy reliability improves, the frequency of intervention declines significantly, indicating increased confidence in autonomous recommendations. Importantly, human oversight does not degrade system performance; instead, it prevents rare but potentially severe failures while preserving learning efficiency. Governance-related outcomes are summarized in Table 9.

Table 9.
Human-in-the-loop governance outcomes

Governance Metric	Early Learning Phase	Mature Learning Phase
Human Intervention Rate (%)	18.6	6.2
Decision Acceptance Rate (%)	81.4	94.7
Performance Loss due to Overrides	Negligible	None

These results demonstrate that human-centric governance complements autonomous intelligence rather than constraining it, aligning closely with the principles of Supply Chain 5.0. The gradual reduction in intervention frequency also suggests that the framework supports effective human–machine collaboration and trust calibration over time. Overall, the results confirm that the proposed DT–HDRL framework represents a fundamental shift from reactive, efficiency-driven supply chain management toward predictive, adaptive, and human-centric decision intelligence. By unifying digital twins, hybrid deep reinforcement learning, and human oversight within a closed-loop architecture, the framework enables real-time adaptability, enhanced resilience, and ethical alignment. These capabilities directly address the limitations of Supply Chain 4.0 systems and provide a practical operationalization of Supply Chain 5.0 principles. The findings therefore contribute both empirically and conceptually to the advancement of intelligent, resilient, and human-centered supply chain management.

FUTURE WORK

While the proposed Digital Twin–enabled hybrid deep reinforcement learning framework demonstrates strong performance in adaptive, predictive, and human-centric supply chain decision-making, several promising directions remain for future research. One important extension involves scaling the framework toward large-scale, multi-enterprise supply networks with decentralized ownership and limited information sharing [31]. Future studies may investigate federated or distributed learning mechanisms that enable collaborative intelligence across organizational boundaries while preserving data privacy and commercial confidentiality. Such extensions would be particularly relevant for global supply ecosystems characterized by fragmented governance and heterogeneous digital maturity. Another avenue for future work lies in enhancing the fidelity and scope of the digital twin. While the current framework focuses on operational and tactical decision layers, future research could integrate strategic planning horizons, including facility location, capacity expansion, and long-term sustainability investment decisions. Incorporating richer behavioral models, such as supplier risk propagation, demand substitution effects, and adaptive consumer behavior, would further improve predictive accuracy and realism [32].

Advances in real-time data integration, including high-frequency sensor streams and external intelligence sources, could also support more granular and responsive digital twin synchronization. From a learning perspective, future work may explore multi-agent reinforcement learning architectures to capture decentralized decision-making across multiple supply chain actors. Such approaches would allow the study of cooperation, competition, and coordination among autonomous agents representing suppliers, manufacturers, logistics providers, and retailers. In addition, incorporating uncertainty-aware and risk-sensitive learning formulations, such as distributional reinforcement learning or robust optimization-enhanced policies, could further improve resilience under extreme disruption scenarios and low-probability, high-impact events. The human-centric dimension of Supply Chain 5.0 also presents important opportunities for further investigation [33].

Future research could examine adaptive human-in-the-loop mechanisms that dynamically adjust the level of autonomy based on system confidence, risk exposure, and operator expertise. Integrating explainable artificial intelligence techniques into the decision pipeline would enhance transparency and trust by providing richer insights into policy rationale and predicted system outcomes. Empirical studies involving real decision-makers could also shed light on cognitive workload, trust calibration, and organizational acceptance of AI-driven supply chain intelligence. Finally, real-world pilot implementations and longitudinal studies represent a critical direction for future work [34]. Deploying the proposed framework in industrial settings would enable validation under real operational constraints, regulatory requirements, and organizational dynamics. Such studies could assess long-term learning behavior, system robustness, and sustainability impacts, providing valuable evidence for the practical adoption of Digital Twin–enabled intelligent supply chain systems. Collectively, these future research directions offer a pathway toward more scalable, resilient, and human-centered Supply Chain 5.0 ecosystems.

CONCLUSION

This study presented a Digital Twin–enabled predictive intelligence framework for Supply Chain 5.0 that integrates hybrid deep reinforcement learning and human-in-the-loop governance within a unified cyber-physical decision architecture. Motivated by the increasing complexity, uncertainty, and disruption exposure of modern supply chains, the proposed framework moves beyond reactive and efficiency-driven paradigms by enabling predictive, adaptive, and human-centric decision management. Through continuous synchronization between the physical supply chain and its digital twin, the framework establishes a closed-loop learning environment in which intelligent agents can anticipate future system states, evaluate alternative actions, and adapt policies in real time. The results demonstrate that embedding hybrid deep reinforcement learning within a continuously updated digital twin significantly enhances decision quality, learning stability, and operational resilience. Compared with traditional optimization-based approaches and standalone reinforcement learning models, the proposed framework achieves superior cost efficiency, higher service levels, and faster recovery from disruptions. These performance gains are achieved without sacrificing stability or transparency, as model-based guidance constrains infeasible exploration and human-in-the-loop oversight ensures ethical alignment and strategic control.

The observed reduction in human intervention over time further indicates that the framework supports effective trust calibration and collaboration between human decision-makers and intelligent systems. From a theoretical perspective, this work contributes to the emerging literature on Supply Chain 5.0 by operationalizing its core principles through a concrete, system-level architecture. The integration of digital twins, hybrid learning, and human-centric governance demonstrates how intelligent autonomy can coexist with transparency, resilience, and ethical accountability. The findings also extend reinforcement learning research by illustrating the benefits of hybridization and cyber-physical learning environments for complex, non-stationary decision problems. From a practical standpoint, the proposed framework offers supply chain managers a scalable pathway toward intelligent, self-optimizing operations capable of responding proactively to uncertainty and disruption.

By transforming digital twins from passive monitoring tools into active decision laboratories, the framework enables organizations to shift from reactive control toward predictive and adaptive management. Overall, this study provides both conceptual and empirical evidence that Digital Twin–enabled hybrid intelligence is a critical enabler of next-generation, human-centric Supply Chain 5.0 systems and lays a robust foundation for future research and real-world deployment.

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