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Supply Chain Cognitive Decision Fabric: An Integrated AI Framework for Real-Time Autonomous Decision Intelligence in Enterprise Retail Operations

Ashok Bandi

Independent Researcher, USA. ORCID: 0009-0007-5442-1424

Abstract

Enterprise supply chains increasingly operate at a pace that outstrips human decision-making capacity. This article introduces the Supply Chain Cognitive Decision Fabric (CDF), a conceptual architecture that integrates machine learning, reinforcement learning, knowledge graphs, and large language models into a unified, layered AI decision system for enterprise retail operations. The CDF is organized across four functional layers (perception, reasoning, decision, and governance), enabling real-time inference from operational signals and the translation of those inferences into auditable, action-ready decisions. Drawing on recent advances in autonomous supply chain intelligence, generative AI integration, and explainability frameworks, the article presents the CDF as a response to the persistent gap between isolated AI tools and enterprise-wide decision coherence. Practitioner evidence from large-scale retail deployments illustrates the operational viability of each layer. The article concludes with implementation guidance, governance requirements, and a research agenda for federated and edge-native extensions of the cognitive decision fabric.

Keywords: Cognitive Decision Fabric, Supply Chain AI, Autonomous Decision Intelligence, Predictive Analytics, Machine Learning, Enterprise Retail, Real-Time Optimization, Knowledge Graph.

1. Introduction

Decision latency is the defining operational constraint of the modern enterprise supply chain. Retail operations at scale generate continuous streams of transactional signals, logistics telemetry, demand indicators, and supplier events - yet the systems that process these signals remain largely siloed. A demand forecasting engine operates apart from a transportation optimization module, which operates apart from a replenishment workflow, which in turn waits on a human decision before any action is initiated. It is this structural mismatch between 'signal' and 'response' that prevents enterprise retailers from being efficient in moving inventory, service levels, and also operational resilience. Cohen et al., 2026.

To address this challenge, academic and practitioner research has aimed at understanding when, how, and why to implement more and more complex uses of AI interventions. Early AI used in the supply chain was focused on predictive analytics and the prediction's level of accuracy when using historical demand data with the help of AI, specifically machine learning techniques (Samuels, 2025). Following that, reinforcement learning agents were introduced, which can optimize the location of inventory under uncertainty (Yang et al., 2025). Finally, a third path has become available most recently: Cognitive augmentation of the decision-making process, where the AI agent suggests a course of action and provides a justification that the practitioner can analyse and validate (Almahri & Xu, 2025; Huq, 2026).

Despite this progress, no unifying architecture has emerged that coordinates predictive, prescriptive, and cognitive AI capabilities into a single, governable enterprise decision system. Individual components are well-documented in the literature; their integration is not. The practical consequence is that enterprise supply chains invest heavily in AI point solutions that remain disconnected from each other and from the operational workflows where their outputs are needed. As Cohen et al. (2026) observe in the most comprehensive practitioner-academic synthesis yet produced on AI in supply chain management, the critical next challenge is not building more AI components; it is achieving the architectural coherence that makes those components operate as a single intelligence.

This article proposes the Supply Chain Cognitive Decision Fabric (CDF) as that architecture. The CDF is not a new algorithm or a new commercial platform. It is a compositional framework specifying how existing AI capabilities should be layered, sequenced, and governed within an enterprise supply chain context. The framework is grounded in the recent literature on autonomous supply chain systems, reinforcement learning, knowledge graph integration, and explainable AI, and is validated against practitioner outcomes from large-scale retail AI deployments.

The article proceeds as follows. Section 2 reviews the evolution of AI in supply chain decision-making. Section 3 introduces the CDF conceptual architecture and defines its four functional layers. Section 4 looks at the implementation framework of enterprise retail. In Section 5, we discuss the concepts of explainability, governance, and human-AI collaboration. Performance measures and operational results are discussed in Section 6. Section 7 outlines challenges and future research directions. Section 8 concludes.

2. Literature Review: Evolution of AI in Supply Chain Decision-Making

2.1 From Optimization to Intelligence

AI and the evolution of the supply chain is a trajectory that continues the already epic evolution of industries from Industry 4.0 to Industry 5.0 and into Industry 6.0. Starting from rule-based automation and statistical forecasting, Samuels (2025) analyzes AI capabilities from 2010 to 2023, highlighting deep learning and reinforcement learning, as well as human-AI collaboration frameworks. The key moment in this transition has not been a change in technology, but architectural: when AI systems evolved and developed as independent systems, the challenge shifted to how to fit them into enterprise business decision processes. Cohen et al. (2026) noted that supply chains relying on a “point and click” approach to AI are consistently outperformed by those with a coherent operational architecture.

This transformation is in line with the general trend of enterprise intelligence. In "An Intersection of AI and Prescriptive Analytics allows Insurers to Improve Supply Chain Resilience," authors Smyth et al. (2024) noted that while AI is increasingly interconnected with other uses in the insurance sector, the biggest disconnect exists between descriptive and diagnostic AI (understanding what happened, why) and prescriptive systems, which offer recommendations and ultimately take corrective measures. Closing that gap requires architectures that coordinate multiple AI capabilities across the full signal-to-action cycle.

2.2 Predictive Analytics and Demand Forecasting

The most well-developed use of AI in the supply chain comes from machine learning-driven demand forecasting. Training transformer-based architectures on multi-stream sensor data signals such as RFID, smart shelf telemetry in retail settings, and IoT, Yang et al. (2025) show, leads to an 18.2% improvement in the reduction of forecast error compared to previous state-of-the-art baselines, while concurrently reducing stockout rates by 23.5%. It is critical that these improvements are not due to improved forecasters' algorithms alone; they are due to close coupling between the forecasters and the downstream inventory optimisation decisions that the forecasts drive. This principle, combining predictive accuracy and prescriptive action, is fundamental in the Cognitive Decision Fabric architecture, which is introduced in this article.

2.3 Reinforcement Learning and Autonomous Inventory Optimization

In high-variability, multi-echelon retail environments, reinforcement learning solutions have yielded steady benefits over classical ones, particularly in the inventory optimization domain. In manufacturing scenarios, Pandey (2026) proposes an autonomous supply chain decision architecture, with four layers: predictive analytics, constraint encoding, scenario simulation, and autonomous execution that is similar to the structure of the CDF proposed here. Without having the demand distribution specified in advance, reinforcement learning agents can learn adaptive restocking policies is particularly relevant to enterprise retail operations, which are usually subject to promotion and seasonality (Yang et al., 2025).

2.4 Knowledge Graphs and Large Language Models for Supply Chain Visibility

The third direction of research in AI for supply chains has been investigating how to leverage knowledge graphs and large language models (LLMs) to enhance visibility and context-related reasoning. By leveraging the capabilities of zero-shot extraction of large language models, Almahri and Xu (2025) show that knowledge graph frameworks can perform named entity recognition with 95% accuracy and supply chain relation extraction with 82% accuracy from unstructured documents, which allows supplier relation maps to be automatically constructed at the tier-2 and tier-3 levels. This capability rectifies one of the long-held shortcomings in quantitative supply chain AI by incorporating unstructured, qualitative supply chain intelligence into decision models.

Furthermore, Simchi-Levi et al. (2026) go on to demonstrate how LLM support can transform supply chain decision platforms by cutting decision-making from days to minutes, by allowing for instantaneous scenario analysis, for real-time updating of models, and automatically rendering a natural language explication of the algorithmic recommendations. For enterprise retail practitioners who must act on AI outputs without deep technical training in the underlying models, this explainability dimension is not a luxury - it is a prerequisite for adoption.

2.5 Integrated Frameworks: Current State and Gap Analysis

Jackson et al. (2024) presented a capability-based interface for generative AI in supply chain management and classified the capabilities that are relevant to supply chain scenarios as content generation, pattern recognition, and simulation. In Ivanov (2026), the analysis is extended to agentic digital twins, that is, AI agents that are incorporated into digital images of physical actors in the supply chain that can learn and act autonomously in their physical world. In Asorose (2025), it is shown that digital twin architectures can be integrated with predictive analytics, enabling the orchestration of the supply chain in a way that is driven by demand and resilient to disruptions.

As detailed by Mohammed et al. (2026), this is the latest illustration of the benefits AI can bring to operational efficiency and sustainability of contemporary retail business, thus reinforcing an increasing trend to focus on AI integration. Moreover, Sun et al. (2024) show that enterprise-level AI transformation on a large scale is positively correlated with enhanced measures of supply chain concentration and risk management results.

What the existing literature does not provide is a unified architecture that coordinates predictive, prescriptive, semantic, and governance AI capabilities into a single coherent enterprise decision system. The Supply Chain Cognitive Decision Fabric is proposed to fill that gap.

3. The Supply Chain Cognitive Decision Fabric: Conceptual Architecture

3.1 Defining the Cognitive Decision Fabric

The Supply Chain Cognitive Decision Fabric (CDF) is a layered AI architecture that helps turn continuous operational data into audit-ready decisions that will be actionable within enterprise retail at a pace, scale, and accuracy that would be unfeasible without AI. The word 'fabric' is chosen deliberately: The CDF is made as strong as a woven fabric, in that it is not the strength of any single one of the components that strengthens the CDF but the coherent integration of multiple AI capabilities – which can be found across a built-in layer model. There are four functional layers in CDF: (1) Perception Layer – which ingests and normalizes the signals that are generated within the operational areas of the company; (2) Reasoning Layer – which applies predictive and diagnostic machine learning models to these normalized signals; (3) Decision Layer – which maps the output from these machine learning models into specific operational recommendations that are compliant with constraints; and (4) Governance Layer – which implements the audit requirements, escalation policies, and human-in-the-loop review protocols. These four layers operate in sequence on individual decision events and in parallel across the enterprise supply chain network.

Connecting all four layers, a knowledge graph functions as the CDF's shared memory, context, and coordination mechanism. In the literature, this design pattern, also known as "Knowledge Graph: Shared context store of a multi-model AI system", is emerging as a highly preferred best practice for enterprise AI architectures that need explainability, auditability, and multi-stakeholder coordination (Almahri & Xu, 2025; Sampathkumar et al., 2026).

3.2 Layer 1: Perception Layer

Perception Layer gathers, normalizes, and forwards operational signals from throughout the enterprise supply chain. These are signal sources like enterprise resource planning (ERP) systems, warehouse management systems (WMS), point-of-sale transactional data, IoT sensor networks on receiving docks, and smart shelves, RFID gate data, transportation management platforms, and externally sourced data such as weather, commodity price data, and geopolitical alerts.

One of the key functions of the Perception Layer is signal quality enforcement: As data flows into the Perception Layer, it is checked against the entity model in the knowledge graph before it gets passed down to the downstream layers. What is required to become operationally material at enterprise scale is for signals to reference unknown SKUs, suppliers, unknown IDs, and/or sensor readings that are too large or too small; such defects are not silently dropped but marked for enrichment (Almahri & Xu, 2025). Validated signals are represented in the knowledge graph as event records and subsequently activate subsequent reasoning processes.

3.3 Layer 2: Reasoning Layer

The Reasoning Layer uses predictive and diagnostic machine learning models to analyze normalized signal data to create probabilistic inferences on future states of supply chains. The inferences comprise forecasts of demand at the SKU-store-day level, quantification of the probability of stockouts, inventory disruption risk scores at the supplier level, and a likelihood assessment of transportation disruption.

The CDF's Reasoning Layer is intended for multi-model composition; that is, a specific group of models is used to perform specific inference tasks, and output is coordinated with the knowledge graph instead of by direct model chaining. Model substitution and incremental capability upgrades are possible without refactoring the architecture; this is one of the distinguishing traits of the AI models of supply chains that meet changing operational demands, according to Samuels (2025). In the enterprise retail space, transformers acting on values from multiple streams of sensor data have proven to deliver significant advantage in demand forecasting, stock positioning, risk mitigation, and supplier reliability scoring (Yang et al., 2025).

3.4 Layer 3: Decision Layer

The Decision Layer integrates inferences generated by the reasoning layer to make operational decisions, considering constraints. In a demand-driven signal, this involves producing a reorder recommendation that maintains the complete constraint set from the enterprise: supplier lead times, transportation capacity, stocks, financial approval limits, and contractual minimum order quantities are just a few examples. In the logistics industry, this means determining what the best route change would be in the face of existing carrier capacity, cost information, and service level commitments.

Prescriptive optimization techniques are used to generate the Decision Layer, such as multi-objective linear programming to optimize inventory and logistics constraints and reinforcement learning to optimize the use of an adaptive policy in a high-variance operating environment (Pandy, 2026). Outputs of the Decision Layer are not raw model predictions; they are fully specified action records: what to do, with which supplier, at what volume, by which date, via which carrier, at what cost, with what impact on projected service levels. These records are registered in the knowledge graph before forwarding to the Governance Layer, creating a complete and queryable audit trail.

3.5 Layer 4: Governance Layer

The Governance Layer is a CDF's risk-management and compliance point of contact. Imposes business rules, finance approval levels, regulatory and escalation policies for each action record generated by the Decision Layer. Actions within pre-approved policy envelopes, based on various pre-calculated factors including financial authority, supplier tier, operational category, and risk score, are forwarded to be executed independently. When an action is outside the policy envelope, it is escalated to a human reviewer, while a natural-language explanation is generated by the LLM component (Simchi-Levi et al., 2026).

Also on the Governance Layer, the CDF's explainability interface is maintained. As Huq (2026) demonstrates, explainable AI mechanisms are a prerequisite for practitioner adoption: a supply chain decision that practitioners cannot interrogate will not be acted upon, regardless of its algorithmic quality. The LLM integration within the Governance Layer generates plain-language summaries of every action record, including the signals that triggered it, the model outputs that shaped it, and the constraints that bounded it, accessible to practitioners at every level of the organization.

4. Implementation Framework: Applying the CDF in Enterprise Retail

4.1 Inventory Planning Modernization

In enterprise retail, the highest-priority application of the Cognitive Decision Fabric is inventory planning. At the scale of large-format retail - thousands of store locations, tens of thousands of active SKUs, hundreds of supplier relationships, and continuous demand variability - the decision volume required for granular inventory management exceeds the capacity of any human planning team. A CDF implementation routes real-time POS data, supplier lead time signals, and warehouse inventory positions through the Perception Layer; applies SKU-level demand forecasting and stockout risk scoring in the Reasoning Layer; generates specific reorder recommendations with full constraint evaluation in the Decision Layer; and enforces financial approval thresholds and supplier tier policies in the Governance Layer.

Enterprises that have modernized inventory planning with AI at retail scale report meaningful gains in operational efficiency and inventory carrying cost, replacing schedule-based replenishment decisions with real-time decisions driven by cognitive inference over live signals (Bailey, 2026; Cohen et al., 2026). These results show the cumulative impact of just-in-time planner buttressing: shorter stockout periods mean no

accumulation of overstocks over the duration of the wait time of the conventional planner process periods, and no accumulation of stockouts over the established replenishment delay periods (Yang et al., 2025).

4.2 Logistics Network Optimization

Each routing decision made in the supply chain logistics – whether shipment assignment, carrier selection, delivery scheduling, or network rebalancing – seems tactical, and yet taken together, this stream of decisions results in transport cost and service level results when scaled up. Configured for logistics optimization, the CDF's Decision Layer renders multi-objective optimization to optimize for multiple objectives: minimizing transportation cost, maximizing on-time delivery, respecting carrier capacity constraints, and keeping the contractual service level commitments across all the active shipment lanes.

A logistics network optimization solution at enterprise retail scale, which combines CDF-pattern architecture and integrates third-party logistics (3PL), has enabled meaningful reductions in transportation cost by eliminating manual review of the logistics network in favor of continuous AI-driven decisions (Asorose, 2025; Mohammed et al., 2026). The disruption risk scoring that the Reasoning Layer provides feeds into the cost optimization results, as well as resilience, because it allows it to make proactive routing changes before a service-level violation occurs due to a carrier failure or a weather event.

4.3 Store-Level Receiving Automation

Many consider inventory receiving at the store to be a very important operational aspect; however, it is underrepresented in the body of literature on AI in Supply Chains. The receiving dock is a critical receiving point for data; receiving the merchandise and registering it into the inventory systems in the right way and in a timely manner has a direct impact on the reliability of the replenishment signal that the CDF's Perception Layer relies on. The knowledge graph's entity model for merchandise and shipments in conjunction with computer vision systems allows for automatic merchandise verification at the point of arrival.

Computer vision capabilities deployed at the receiving dock can meaningfully accelerate merchandise verification across large enterprise store networks, providing more accurate and timely inventory signal information to the CDF's Perception Layer. Workforce efficiency and enhanced data quality are two immediate advantages of CDF automation at the signal acquisition layer, and they further ramp up in downstream benefits as the CDF moves through the reasoning and decisions downstream.

4.4 Cross-Functional Data Orchestration

The CDF's analytical effectiveness depends on clean, timely data flowing from multiple enterprise systems. Enterprise retail environments characteristically operate heterogeneous technology stacks - ERP, WMS, TMS, POS, supplier portals, and analytics platforms, none of which were designed to interoperate at the signal latency the CDF requires. In order to implement CDF, a data orchestration layer is needed to link multiple data source systems with standardized API contracts, event streaming infrastructure, and event quality governance protocols that provide normative properties on data signals originating from various source systems to the Perception Layer (Jackson et al., 2024; Sampathkumar et al., 2026).

The principle of the architecture behind this layer of orchestration is that although the orchestration layer is an important key piece of the puzzle, the knowledge graph is the ultimate authority dictating who is who and which structure of relationship. The orchestration layer routes signals; the knowledge graph resolves entity references, validates relationships, and forwards to downstream layers in the CDF. If the supply chain entity universe evolves, the orchestration layer is not going to be a semantic bottleneck because of this separation of concerns.

5. Explainability, Governance, and Human-AI Collaboration

5.1 Explainable AI in Supply Chain Decisions

Deploying autonomous decision systems in enterprise supply chains raises a fundamental adoption challenge: how do practitioners evaluate and trust AI-generated recommendations they cannot directly inspect? The explainable AI research community has produced a range of model-level techniques - attention mechanisms, SHAP value decompositions, counterfactual explanations, and natural-language generation. The CDF's style of explainability is architectural and not per-model; this is because they aim to embed transparency into the data flow between the layers instead of adding it as an "afterthought" to existing models once they had been trained (Huq, 2026).

Each action record traversed by the CDF contains a provenance chain, consisting of the actions from the Perception layer that started it, inferences from the Reasoning layer that formed it, constraints from the Decision layer that bounded it, and policies from the Governance layer that approved or escalated it. At the time of review, this traceability chain is accessible via the LLM component (presenting a summary of the traceability

chain as a practitioner-readable element). This architecture allows for the level of explainability to grow in proportion to the number of actions in the governance queue; the 1000th governance action is as explainable as the 1st action (Simchi-Levi et al., 2026).

5.2 Human-in-the-Loop Governance

The CDF does not support absolute autonomy of AI. The governance structure recognises three types of decisions: these are autonomous; these are semi-autonomous calls which need practitioners' affirmation before use; and these are escalated decisions which must be monitored by managers. There is no strong boundary between these categories; it depends on how well the CDFs do in a given decision space, what confidence intervals are provided by the Reasoning Layer, and what financial/operational related risks the decision poses.

This maturing autonomy process exemplifies a critical notion that AC literature has long known: the attributes of AI autonomy in supply chains are not either-or, but exist on a continuum (Cohen et al., 2026). Early in a CDF deployment, most decisions will route through semi-autonomous review, building practitioner confidence and generating the human-labelled decision data required to validate and refine Reasoning Layer models. As model performance is validated and policy envelopes are calibrated against operational outcomes, the proportion of fully autonomous decisions grows. The Governance Layer enforces this progression in a controlled, auditable manner that preserves accountability throughout the transition.

5.3 Audit Trails and Regulatory Compliance

Enterprise retail operations are subject to regulatory requirements: financial reporting, consumer and data privacy, that impose audit trail obligations on operational decision systems. The CDF's knowledge graph architecture provides a natural compliance foundation: every decision event is registered with a complete provenance record, creating an immutable audit trail that satisfies regulatory documentation requirements. Working with this is a real-world problem that many existing supply chain use cases using AI have: The AI system receives inputs, processes through some parameters, and follows particular policies; The details might not be documented after the fact, and no out-of-the-box solution exists to audit the model back to the inputs, parameters, and policy constraints (Ivanov, 2026).

6. Performance Metrics and Operational Outcomes

6.1 Decision Latency Reduction

The most important performance metric to consider for the CDF is the time it takes from a signal in a supply chain to an operational action. Latency for typical replenishment or network routing decisions in a conventional human-facilitated supply chain decision workflow is hours, weeks, or days. CDF implementations eliminate the delays in the 'signal to action' cycle associated with decisions in the policy envelope, cutting the delay to minutes or seconds, which is 2 or 3 orders of magnitude lower than the hours or days it can take when relying on traditional methods (Simchi-Levi et al., 2026).

6.2 Inventory Efficiency and Cost Impact

A pilot of enterprise retail-scale inventory planning using the CDF pattern has yielded a substantial increase in operational efficiency and a meaningful reduction in inventory carrying cost. The decision latency reductions discussed in Section 6.1, when replenishment signals happen quickly, and the reduction in stockout accumulation and overstock buildup, which may arise from batch-scheduled and manually reviewed inventory cycles, are the direct outcomes.

6.3 Logistics Cost and Service Level

At enterprise retail scale, Continuous, CDF-pattern logistics network decision-making has proven transportation cost savings of \$50M annually alongside concurrent service-level improvements thanks to the disruption risk scoring capability enabled by the Reasoning Layer, where carrier failures and weather events don't have to impact service-level in real-time (Asorose, 2025). These logistics outcomes illustrate the prescriptive value of tightly coupling the Reasoning Layer's predictive risk outputs with the Decision Layer's optimization engine.

6.4 Scalability Considerations

A defining property of the CDF architecture is horizontal scalability. Because individual AI components are deployed as modular layers behind the knowledge graph's entity resolution interface, the system scales without architectural refactoring: additional decision domains - new product categories, new geographic markets, new logistics lanes - are onboarded by extending the knowledge graph's entity model and configuring domain-specific model instances in the Reasoning Layer. For enterprise retail, the property of scalability is

crucial as the supply chain continually grows in scale and in its dynamic structure (Ivanov, 2026; Sampathkumar et al., 2026).

7. Challenges and Future Directions

7.1 Data Quality and Interoperability Barriers

The level of analysis provided by the CDF does depend on the quality of the data added to the Perception Layer. The ERP transactions don't always get completed by the deadline in enterprise environments, sensor data from the IoT devices is often unreliable, data formats from suppliers are inconsistent, and reporting from third-party logistics is slow. To overcome these data quality challenges, data governance infrastructure needs to be invested in – and this is a prerequisite that needs to be incorporated in CDF implementation projects from the beginning instead of later on in the project's lifecycle (Jackson et al., 2024).

This interoperability issue is exacerbated by multi-supplier, multi-carrier operations, with multiple data standards not uniformly embraced. Full resolution would require supplier and carrier onboarding standards that would offer a consistent data exchange format and API contract for all trades in the trading partner network – a knowledge graph if a part of the solution.

7.2 Organizational Transformation and Workforce Development

A CDF transforms a practitioner of a supply chain from transactional decision makers into a system supervisor. Methods and competencies that were previously utilized to resolve hundreds of individual replenishment/routing decisions daily are to be replaced with policy calibration, governance review, exception triage, and model performance monitoring skills (Samuels, 2025; Bailey, 2026). These capabilities rely on an analytical approach rather than transactional ones and will push supply chain teams to gain a systems view of how the different parts of AI can fit within the CDF.

The workforce transformation challenge is fundamentally a role redesign problem, not merely a training one. Organizations that deploy CDFs without redesigning the job functions that interface with the Governance Layer will find that review queues become human bottlenecks that reproduce the very latency the CDF was designed to eliminate (Cohen et al., 2026).

7.3 Edge AI and Real-Time Processing at Scale

As the CDF is deployed across increasingly distributed supply chain networks - thousands of store locations, hundreds of distribution centers, dozens of logistics partners - data processing and inference workloads must move progressively closer to the operational edge. Edge AI architectures, distributing model inference to store-level or vehicle-level compute rather than centralizing processing in a cloud environment, are required to maintain the CDF's low-latency decision capability at full enterprise scale. Today, achieving consistency between edge inference decisions and the global state of the knowledge graph in the central system is still an open system architecture research question.

7.4 Federated Learning for Cross-Enterprise CDF

Multi-enterprise supply chain networks are an extension in a passing sense of the CDF concept, and are environments in which various entities making up the network (frequently including manufacturers, distributors, retailers, and logistics providers) have a shared cognitive decision architecture while maintaining data privacy barriers between operational entities. Transitional approaches, like federated learning methods, which can be used to train machine learning models across decentralized data without bringing all data to a single location, can lead the way in successfully deploying a cross-enterprise CDF. Federated learning combined with knowledge graph-based entity resolution may facilitate the interoperability of learning of leagues from industry-scaled supply chain ecosystems, of which important implications could follow in areas of supply chain resilience and effectiveness (Ivanov, 2026; Smyth et al., 2024).

8. Conclusion

The Supply Chain Cognitive Decision Fabric represents a timely and practically grounded response to the central operational challenge of contemporary enterprise retail: the persistent gap between the volume and velocity of supply chain signals and the organizational capacity to convert those signals into timely, intelligent, and accountable decisions. By integrating predictive analytics, prescriptive optimization, semantic reasoning through knowledge graphs, and large language model-powered explainability within a four-layer architecture, the CDF enables continuous, autonomous, and auditable decision-making across the full supply chain operations cycle.

The cognitive decision fabric is not a replacement for supply chain expertise; it is the architecture through which that expertise is operationalized at the scale and speed modern enterprise retail requires. There is a lot

of evidence from the recent literature, and many sources of AI deployments in large retail companies, that lead on the performance of these supply chains are not necessarily the organizations that deployed the most AI components, but those that put AI into coherent decision architectures. Governed by rigorous human oversight (Cohen et al., 2026; Samuels, 2025). The CDF is proposed as the template for that integration.

Future research should address federated CDF implementation across multi-enterprise supply chain networks, edge-native deployment architectures for distributed retail environments, and the long-term workforce competency models required to sustain cognitive supply chain operations at enterprise scale.

Conflict of Interest

The author declares no conflict of interest.

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