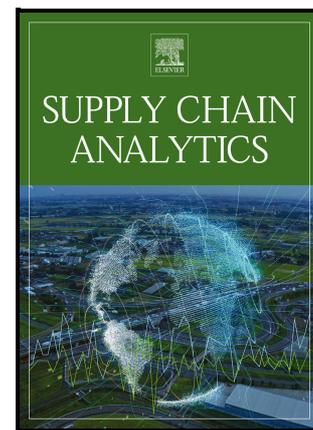


A Data-Driven and Cognitive Analytics Framework for Sustainable Supply Chain Transformation in Industry 6.0

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A Data-Driven and Cognitive Analytics Framework for Sustainable Supply Chain Transformation in Industry 6.0

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Abstract

The transition from data-driven to cognitively adaptive supply chains represent a critical step toward Industry 6.0, where learning, coordination, and sustainability must be addressed jointly. Existing supply chain analytics approaches remain limited in capturing adaptive and systemic behaviors under uncertainty, particularly in resource- and energy-intensive industrial contexts. This study proposes a Cognitive and Data-Driven Framework for Supply Chains based on federated learning and synthetic data simulations grounded in aggregated industrial benchmarks. The framework introduces the Adaptivity Coefficient (A_c), a composite metric integrating learning velocity, anticipatory responsiveness, and technological exposure to quantify cognitive readiness at the network level. Results from simulation experiments show that cognitively adaptive supply chains achieve significant performance improvements compared to conventional predictive approaches. Specifically, cognitive coordination reduces cumulative disruption costs by 18–25%, lowers emissions intensity by up to 15%, and shortens recovery time by approximately 27%. The analysis further demonstrates that adaptive learning expands the Pareto-efficient frontier, enabling simultaneous gains in cost efficiency, resilience, and environmental performance under varying levels of uncertainty. These findings suggest that cognitive adaptivity functions as a strategic capability rather than a purely technical feature. The study concludes by highlighting the managerial and policy implications of embedding cognitive learning into supply chain governance and by outlining pathways for future empirical validation in hard-to-abate manufacturing sectors.

Keywords: Agentic AI; Cognitive Adaptivity; Supply Chain Analytics; Industry 6.0; Federated Learning; Predictive Analytics; Sustainable Supply Chains; Hard-to-Abate Industries

Highlights

- A Cognitive and Data-Driven Framework is proposed to model Industry 6.0 supply chains.
- Synthetic data and federated learning are used to simulate adaptive and sustainable behaviors.
- The Adaptivity Coefficient (A_c) quantifies network readiness and cognitive performance.
- Cognitive adaptivity simultaneously improves cost efficiency, resilience, and environmental outcomes.
- The study outlines governance and validation pathways for systemic change in hard-to-abate industries.

1. Introduction

Global supply chains are facing structural transformation. For more than two decades, analytics and automation have improved visibility, forecasting, and efficiency of operations [1], yet most supply networks remain fragmented and reactive. In this study, the object of analysis is the coordination of decision-making and learning across multi-tier supply networks to improve efficiency, resilience, and sustainability outcomes under uncertainty, with a focus on hard-to-abate manufacturing contexts [2].

To situate this transition, it is useful to frame supply chains within the broader industrial evolution: Industry 3.0 consolidated automation through early digital control; Industry 4.0 scaled connectivity (IoT) and predictive analytics; Industry 5.0 re-centered human value and human–machine collaboration; and Industry 6.0 extends these foundations by treating supply networks as learning systems that must co-evolve with environmental and societal constraints [3].

Accordingly, the transition toward Industry 6.0 introduces a different logic: supply chains are not only data-driven reactive systems but cognitive supply chains that learn, anticipate, and co-evolve dynamically with their environment [4,5]. In this new paradigm, decision-making is no longer centralized in predictive models but distributed across intelligent nodes that share information, adapt in real time, and align with broader sustainability goals [6]. The shift from predictive to cognitive supply chains is

more than a technological progression. It signals a conceptual evolution in how data, learning, and sustainability interact. Predictive analytics, typical of Industry 4.0, focused on anticipating fluctuations and minimizing variance. Cognitive analytics, emerging under Industry 6.0, extends this approach by embedding continuous learning and human-AI co-evolution into supply chain design. The result is a form of operational intelligence that not only reacts to data but transforms it into adaptive knowledge [7].

Despite rapid advances in data infrastructure, the integration of cognitive adaptivity within supply chains remains fragmented [8]. Firms collect vast amounts of information but still struggle to translate it into coordinated cross-organizational intelligence. Research in federated learning and multi-objective optimization offers promising avenues, allowing distributed networks to learn collectively while preserving autonomy and data privacy [9]. Here, “distributed learning” refers to multi-actor settings where supply-chain partners train or update shared models without pooling raw data, enabling collective intelligence while reducing confidentiality and governance barriers. However, a coherent framework that connects these techniques with measurable indicators of cognitive maturity and sustainability performance is still missing [10].

This paper addresses that gap. It proposes a Cognitive Supply Chain Framework designed to operationalize the principles of Industry 6.0. Our contribution is threefold: (i) we conceptualize cognitive adaptivity as a system-level capability linking data, learning, and sustainability; (ii) we introduce the Adaptivity Coefficient (A_c) as a novel measurable indicator of cognitive maturity; and (iii) we demonstrate a controlled validation pathway using synthetic-data simulations and distributed learning architectures designed for reproducibility and transferability.

The framework introduces the A_c , a metric that captures the learning velocity, anticipatory responsiveness, and technological exposure of supply networks [11]. These dimensions are interdependent: cognitive adaptivity emerges when learning and anticipation scale in step with exposure and complexity, rather than improving in isolation [12]. To validate the framework and proposed metric, synthetic data simulations are conducted to reproduce dynamic interactions among suppliers, manufacturers, and distributors in hard-to-abate sectors [13]. The use of synthetic data, explicitly declared and methodologically controlled, allows for testing the framework’s scalability, reproducibility, and transferability across industrial contexts [14]. Importantly, positioning synthetic data as part of the methodological contribution helps address common multi-firm constraints such as low-data availability and privacy restrictions [15].

The framework primarily targets hard-to-abate manufacturing sectors such as ceramics [16], steel [17], and cement [18], where energy intensity, process heat, and emissions are structurally high. These sectors are increasingly used as testbeds for studying the joint problem of decarbonization, resilience, and operational learning under uncertainty [19]. These industries provide ideal testbeds for exploring cognitive adaptivity, since their production systems combine rigid process constraints with the need for continuous optimization across material, energy, and data flows. The study pursues three research questions:

- **RQ1:** How can cognitive adaptivity be defined and measured in the context of data-driven supply chains?
- **RQ2:** How can federated learning architecture enhance collective intelligence while maintaining data security and privacy?
- **RQ3:** How can these cognitive mechanisms contribute to systemic sustainability, linking operational analytics to environmental and social goals?

By addressing these questions, the paper seeks to bridge the analytical rigor of supply chain modeling with the human and systemic dimensions of Industry 6.0. At the same time, we acknowledge that human value -particularly trust, incentives, and governance enabling information sharing- is not yet captured by consolidated visibility models in hard-to-abate industrial ecosystems; accordingly, we treat this as a key limitation and a priority avenue for future research [20].

Section 2 (Literature review) synthesizes prior work and positions the A_c as the unifying construct; Section 3 (Methods) details the synthetic-data generation, federated learning setup, and the operationalization of A_c ; Section 4 (Results) reports findings; Section 5 (Discussion) compares results

with the literature and consolidates limitations; and Section 6 (Conclusions) summarizes contributions and future research directions.

2. Literature review: From Data-Driven to Cognitive Supply Chains

Industrial evolution has always reflected the shifting relationship between technology, organization, and know-how. Industry 3.0 introduced automation through early digital control [21] while Industry 4.0 expanded the paradigm with IoT, predictive analytics, and real-time optimization [22]. Industry 5.0 emphasized collaboration between humans and intelligent machines, restoring flexibility and human value in automated environments [23]. Industry 6.0, now taking shape, adds a new dimension in which learning, adaptation, and sustainability operate as one integrated cognitive process. In this emerging context, supply chains cease to be reactive infrastructures that execute data-driven forecasts [24]. They become cognitive ecosystems where information, learning, and decision-making evolve together.

The digitalization transition, which involves IoT, AI, Cloud Computing, and Blockchain, improves real-time visibility and data integrity in supply chains, enabling them to shift from reactive risk management to anticipatory, coordinated approaches [25]. Rather than optimizing each node in isolation, cognitive supply chains coordinate distributed intelligence to perceive weak signals, anticipate disruptions, and strengthen resilience aftershocks [26]. This transition redefines the very meaning of efficiency, linking economic performance with environmental and social coherence. In this framing, sustainability is not merely a compliance constraint: a dynamic system property that must be governed through feedback, learning, and coordinated decision-making across firms [27]. In this context, the adoption of advanced mathematical programming and optimization models emerges as a pivotal enabler for sustainable operations; such approaches are increasingly recognized not only in manufacturing but also in agriculture and food systems, where linear reformulation techniques have demonstrated substantial improvements in both efficiency and scalability [28]. Recent research highlights that sustainable transformation requires not only technological innovation but also the active engagement of communities and new generations, as well as collaborative strategies, to achieve systemic change and long-term impact [29,30].

The distinction between predictive and cognitive models lies in the type of intelligence they embody [31]. Predictive analytics extrapolate future states from past regularities; cognitive analytics continuously update internal representations as new data and contexts emerge [32]. Adaptivity, rather than accuracy alone, becomes the decisive capability [33]. In turbulent environments, strong predictive accuracy can coexist with weak coordination, making adaptivity a more informative system-level capability than prediction alone [34]. Networks that learn faster than the rate of environmental change can maintain systemic stability even in the face of turbulence [35]. Hence, learning velocity and anticipatory responsiveness evolve into measurable sources of competitive advantage.

To move from a conceptual description to a measurable view of cognitive supply chains, the literature suggests focusing on three interdependent dimensions that recur across analytics, resilience, and complexity perspectives: Learning Velocity (L_v), Anticipatory Responsiveness (A_r), and Technological Exposure (T_e) [36].

- i. L_v refers to how quickly the network can update models and decisions as new information arrives, especially when learning must occur across multiple actors under privacy constraints [37].
- ii. A_r captures the ability to detect weak signals, align interpretation across nodes, and trigger proactive adjustments before disruptions fully materialize [38].
- iii. T_e represents the challenge load faced by distributed learning and coordination, including heterogeneity in digital maturity, interoperability frictions, data fragmentation, cybersecurity constraints, and volatility of operating conditions [39].

Crucially, these dimensions must evolve jointly: increasing exposure without proportional gains in learning and anticipation reduces adaptivity, while isolated improvements in L_v or A_r may not translate into network-level coordination [12].

This shift also transforms sustainability. In traditional supply chain management, sustainability was framed as a constraint or compliance target [40]. Within the cognitive paradigm, it turns into a dynamic

property of the system: the ability of a network to regenerate its economic and ecological efficiency through feedback and learning [41]. Sustainability thus depends not only on cleaner technologies or optimized flows but on the cognitive readiness of the entire ecosystem. This framing motivates the need for a unifying construct that links L_v , A_r , and T_e to systemic sustainability outcomes rather than treating them as separate “partial improvements” [27].

Existing research provides fragments of this picture. Studies on federated learning demonstrate that distributed models can achieve global optimization without sharing raw data, supporting privacy and autonomy across firms [42]. In cognitive terms, federated learning can strengthen network-level L_v by enabling iterative, privacy-preserving model updates across organizational boundaries [43]. Multi-objective optimization frameworks explore how economic, environmental, and resilience goals can be reconciled under uncertainty [44], while simulation-based digital twin frameworks that incorporate real-time data, discrete-event simulation, and machine learning support dynamic decision-making and resilience during disruptions [45]. These approaches can strengthen A_r by enabling faster sense–learn–respond cycles, yet they often do not provide an interpretable indicator of whether the network is becoming more cognitively mature over time [46].

At the same time, T_e -digital maturity heterogeneity, interoperability frictions, data fragmentation, and cybersecurity/privacy constraints- often grows faster than organizational learning capabilities, increasing the difficulty of coordinated learning and anticipation at the network level [39]. This is why T_e must be treated as a scaling pressure rather than a background condition: without explicitly accounting for exposure, improvements in L_v and A_r may be insufficient to sustain adaptivity under Industry 6.0 conditions [12].

Nevertheless, even when technical constraints are mitigated, information sharing across firms remains constrained by human and organizational factors such as trust, incentives, and governance. Because robust, sector-specific models to quantify this dimension of informational visibility are still underdeveloped in hard-to-abate industrial ecosystems, it is treated here as a key limitation and a future research direction rather than as a fully operationalized dimension of A_c [20].

Finally, these contributions often remain unconnected, lacking a unifying construct to describe how a supply chain learns and adapts collectively. Industry 6.0 offers that unifying perspective. It conceptualizes supply chains as learning systems, where human insight, artificial reasoning, and environmental feedback form a single cognitive loop [4]. Within this loop, value is not extracted from data but co-created through shared understanding and anticipatory coordination [14]. Building on this view, the present study proposes the A_c as the unifying indicator that closes the gap: A_c integrates L_v and A_r as capability drivers, while explicitly accounting for T_e as the scaling pressure that conditions how much adaptivity can be realized at the network level [12,36]. In this way, A_c consolidates prior par advances (distributed learning, optimization, simulation) into a single interpretable measure of cognitive maturity and provides a basis for linking cognitive readiness to systemic sustainability outcomes [27].

The following section outlines the methodological foundations of this approach, focusing on how synthetic data and generative modeling enable the controlled testing of cognitive behaviors in complex supply-chain networks [15].

3. Methods: Synthetic Data, Federated Learning, and Cognitive Supply Chain Framework

The methodological design of this study reflects a dual requirement: analytical rigor and systemic realism. Industry 6.0 supply chains are complex, adaptive, and context-dependent systems that cannot be captured through static datasets or isolated case studies alone. Their cognitive behavior (learning, anticipation, and adaptation) unfolds over time and across distributed agents. To explore these dynamics under controlled and replicable conditions, the study adopts a synthetic data approach supported by generative artificial intelligence [47]. Synthetic data are not a substitute for empirical observations, but a structured means to reproduce the variability, uncertainty, and nonlinearity typical of real industrial networks. As highlighted in the recent systematic review [48], generative models such as variational autoencoders, generative adversarial networks (GANs), and diffusion models can generate realistic datasets that preserve statistical consistency while protecting data privacy and enabling scalability [49]. The present work follows this methodological lineage, using synthetic data as a bridge between conceptual modeling and practical validation. Building on this controlled simulation

setting, the method then operationalizes cognitive supply-chain behavior through (i) a three-layer CSC architecture (perceptive–cognitive–sustainability) and (ii) the Adaptivity Coefficient (A_c), which tracks how learning and anticipation evolve under technological exposure [5,50].

3.1. Rationale for Synthetic Data

Empirical data on cognitive coordination are limited and unevenly distributed across industries. In hard-to-abate, confidentiality requirements restrict the distribution of operational or environmental information [51]. Synthetic data overcomes these barriers by allowing the simulation of learning interactions, disruption patterns, and adaptive responses without exposing sensitive information. They also permit systematic regulation of parameters such as demand volatility, lead times, or carbon intensity, enabling controlled experimentation on network behavior. Within this research, the synthetic dataset serves three purposes:

- i. to test the scalability of the Cognitive Supply Chain (CSC) Framework under varying network sizes and interdependencies.
- ii. to examine the sensitivity of the Adaptivity Coefficient (A_c) to fluctuations in learning velocity, anticipation, and technological exposure.
- iii. to assess multi-objective trade-offs among cost, emissions, and resilience in federated decision environments.

Synthetic data were employed to create a controlled environment that isolates complex causal mechanisms to observe in real industrial settings. The purpose of this configuration is exploratory rather than predictive, allowing the framework to test dynamic relationships before their empirical implementation. Future work will extend this validation through pilot studies with industrial partners, where real operational and environmental data can be progressively integrated into the simulation model.

3.2. Data Generation and Validation Process

The synthetic data pipeline follows a structured sequence inspired by recent developments in generative AI:

- **Parameter definition.** Baseline distributions are derived from aggregated industrial benchmarks, including production volumes, demand cycles, transport distances, energy use, and emission factors [52].
- **Generative modeling.** Conditional GANs (cGANs) generate multi-node datasets in which each agent (supplier, manufacturer, distributor) is described by correlated variables for cost, time, energy, and environmental performance [53]. Conditioning variables are used to control scenario regimes across nodes and time (e.g., volatility and exposure levels).
- **Coherence validation.** Generated data are compared against reference distributions using Kullback–Leibler (KL) divergence and Pearson correlation coefficients, ensuring distributional realism and the preservation of inter-variable relationships [54].
- **Learning architecture.** Synthetic datasets feed a federated learning setup in which each node trains a local Long Short-Term Memory (LSTM) time-series model and shares model parameters with a central aggregator, rather than raw data, to preserve confidentiality while enabling collective learning [11].
- **Adaptivity assessment.** The Adaptivity Coefficient (A_c) is computed at each training iteration to track the evolution of cognitive maturity across nodes and simulation rounds [55].

This pipeline ensures methodological transparency and reproducibility. The explicit declaration of synthetic data usage prevents ambiguity between simulation and empirical inference, aligning with the ethical and scientific standards of data-driven research. To further support replicability, the study distinguishes clearly between (i) synthetic-data realism checks (distributional coherence), (ii) federated training dynamics (local-to-global updates), and (iii) system-level evaluation via A_c and the multi-objective sustainability function described below.

3.3. Federated Learning Setup and Cognitive Modeling Perspective

The cognitive behavior of the supply network is modeled as an emergent property of distributed learning processes [56]. Each node is viewed as an adaptive agent that adjusts its decision parameters based on feedback from both local performance and global trends shared through the federated model. Over time, these local adjustments generate collective patterns of adaptation, as measured by the Adaptivity Coefficient (A_c).

This approach merges machine learning with systems thinking data patterns are treated as representations of cognitive interactions, while performance indicators evolve through feedback and reinforcement. Accordingly, the learning process is implemented as a standard cross-silo federated configuration in which each supply-chain node trains locally on its time-series data, transmits model parameters (rather than raw data) to a central aggregator, and receives an updated global model after aggregation. Aggregation follows the Federated Averaging (FedAvg) protocol, which computes a weighted average of local updates to produce the global model that is redistributed to participating nodes [57].

3.4. Cognitive Supply Chain Architecture and Operationalization of the Adaptivity Coefficient

The proposed framework interprets the supply chain as a cognitive architecture capable of perceiving, learning, and adapting to its environment [58]. It extends the classical view of a supply chain as a flow of materials, information, and finances by adding a fourth, dynamic dimension: knowledge circulation [49]. In this sense, each firm becomes both a producer and a receiver of cognitive signals, contributing to a distributed intelligence that evolves. To operationalize this architecture in an interpretable way, we structure the CSC system into three interacting layers—perceptive, cognitive, and sustainability—aligned with established “sense–think–act” and information-to-decision perspectives (i.e., data-information-insight-action) [59]. These layers clarify how signals are selected (perceptive), transformed into learning and coordination (cognitive), and translated into multi-objective trade-offs (sustainability).

3.4.1. Perceptive Layer: Data as Context

The perceptive layer captures the continuous flow of signals from internal and external sources. It includes sensor networks, Enterprise Resource Planning (ERP) systems, logistics data, and market indicators, as well as contextual variables such as energy prices, emission factors, and regulatory changes. Unlike traditional data acquisition systems that focus on volume and frequency, this layer emphasizes relevance and contextual alignment. Data are not collected indiscriminately; they are selected for their contribution to situational awareness. Within the synthetic data environment, operational variables are generated to simulate fluctuations in demand, production, and energy intensity, enabling the system to respond to realistic, interdependent patterns. This layer establishes the informational foundation upon which higher levels of cognition operate.

3.4.2. Cognitive Layer: Distributed Learning and Adaptivity

The cognitive layer represents the analytical and decision-making core of the system. Here, federated learning serves as the operational backbone. Each node (supplier, manufacturer, or distributor) trains a local predictive model using its own synthetic dataset and periodically shares only the learned parameters with an aggregator. The aggregator consolidates these updates into a global model, which is then redistributed to all participants. This mechanism enables a collective intelligence that preserves privacy while fostering cooperation. Learning becomes an emergent process rather than a centralized computation. Each iteration refines both local accuracy and global coordination, creating a feedback loop that mirrors how cognition develops in natural systems.

To quantify the dynamics of this process, the study introduces the Adaptivity Coefficient (A_c), defined as:

$$A_c = \frac{L_v + A_r}{T_e}$$

Where:

- L_v (Learning velocity) measures the rate at which each node improves its forecasting performance over time.
- A_r (Anticipatory responsiveness) represents the capacity to adjust decisions before external disruptions fully manifest.
- T_e (Technological exposure) quantifies the complexity and frequency of technological changes that the system must absorb, including digital maturity heterogeneity, interoperability frictions, data fragmentation, and cybersecurity/privacy constraints.

The structure of A_c reflects the theoretical logic introduced in the literature review: L_v and A_r are complementary capability drivers (faster learning and earlier response both increase adaptive capacity), whereas T_e acts as a scaling pressure that increases the difficulty of sustaining coordinated adaptivity as exposure and complexity rise [50]. Accordingly, A_c increases when the network improves learning and anticipation proportionally to exposure; conversely, if T_e rises faster than L_v and A_r , adaptivity declines by design—capturing the “capability–exposure balance” principle [12,50].

The coefficient is normalized across the network using min–max scaling per simulation round, yielding a value between 0 and 1, where higher values indicate a more adaptive and cognitively mature supply chain. It thus functions as a meta-indicator of cognitive readiness, linking analytical performance with organizational learning.

3.4.3. Sustainability Layer: Multi-Objective Integration

The third layer integrates sustainability into the cognitive process rather than treating it as an external constraint. The system simultaneously optimizes three objectives: economic efficiency (C), environmental performance (E), and resilience (R). These are modeled through a multi-objective function:

$$\text{Minimize } F = \lambda_1 C + \lambda_2 E - \lambda_3 R$$

Where λ_1 , λ_2 , and λ_3 are dynamic weights reflecting strategic priorities and regulatory contexts. The negative sign associated with resilience indicates its positive contribution to overall performance. This formulation allows the network to balance cost reduction, emission mitigation, and adaptive capacity under varying conditions. Over simulation rounds, the federated model identifies Pareto-optimal configurations where trade-offs among objectives converge. The learning process thus aligns not only with short-term efficiency but also with long-term systemic balance.

3.4.4. Interaction and Feedback

The three layers interact through continuous feedback loops. Data from the perceptive layer feeds the cognitive layer, where learning models update predictive and prescriptive insights. These, in turn, inform decisions in the sustainability layer, influencing resource allocation, routing, or energy mix. The results of these actions re-enter the perceptive layer as new data, closing the cognitive loop. This cyclical flow of perception, learning, and adaptation defines the essence of a CSC Framework. It embodies the principles of Industry 6.0 by coupling analytical intelligence with environmental awareness. Adaptivity, in this view, becomes both a technical and organizational capability: the ability of an industrial ecosystem to evolve without eroding the conditions that sustain it. The architecture is organized into perceptive, cognitive, and sustainability layers connected by feedback loops, as illustrated in Figure 1.

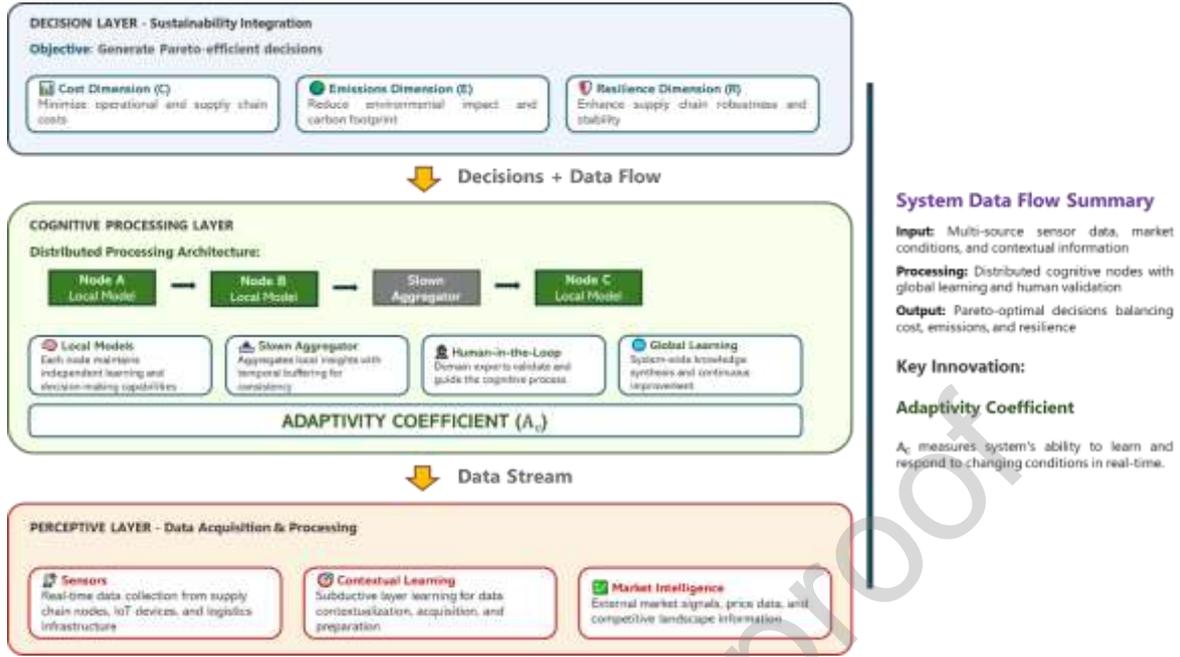


Figure 1: Cognitive Supply Chain Framework.

The framework comprises three interacting layers. The perceptive layer integrates contextual data sources, including sensors, ERP systems, IoT devices, market indicators, and energy and emissions data. The cognitive layer implements federated learning with a global aggregator and local models and quantifies network readiness using the Adaptivity Coefficient $A_c = (L_v + A_r)/T_e$. The sustainability layer integrates cost, emissions, and resilience in a multi-objective decision process. Arrows show upward information flow and feedback from decisions to data. Each local node trains an LSTM-based predictive model on its time-series data and transmits only model weights to a global aggregator, instead of private data. The central aggregator employs Federated Averaging protocol to perform a weighted averaging of local parameters, effectively consolidating global patterns into a unified model which is then redistributed to all participating nodes for further refinement. This iterative cycle preserves data privacy while enabling global optimization through decentralized learning, as depicted in the cognitive layer of Figure 1.

3.4.5. Conceptual Validation through Synthetic Simulation

The conceptual framework is validated through the synthetic data simulations described in the methodology. Each run corresponds to a virtual scenario with different levels of demand volatility, technological change, and environmental pressure. Across these scenarios, the model evaluates how variations in L_v , A_r , and T_e affect the Adaptivity Coefficient and, in turn, how this influences the multi-objective performance function. Preliminary results, discussed in the next section, indicate that networks with higher adaptivity not only achieve better predictive accuracy but also display faster recovery after disruptions and lower cumulative emissions intensity. This correlation supports the view that cognitive adaptivity is a measurable driver of systemic sustainability.

3.5. Methodological Integrity and Limitations

Although synthetic data enable conceptual testing and cross-scenario analysis, they cannot fully replace empirical validation [60]. Their strength lies in isolating causal mechanisms and exploring boundaries of model behavior rather than reproducing real-world outcomes with absolute precision. Future research should therefore complement this approach with hybrid datasets combining synthetic and real observations to refine parameter calibration and contextual accuracy. The methodological framework combines the analytical robustness of generative AI with the systemic perspective of cognitive modeling [61]. It enables the controlled exploration of adaptivity in complex supply networks and provides the foundation for the results presented in the next section.

3.6 Synthetic Data Generation and Reproducibility

The empirical analysis employs simulation experiments on synthetically generated datasets, reflecting the study's exploratory and theory-building focus, as well as the scarcity of harmonized multi-tier supply chain data integrating operational, logistical, and environmental dimensions. To ensure realism, synthetic data are derived from aggregated industrial benchmarks rather than arbitrary assumptions. Production volumes and demand cycles follow trend- and seasonality-adjusted stochastic processes, while transport distances are modeled using bounded lognormal distributions to capture the asymmetric and spatially constrained nature of logistics networks. Energy consumption and emission factors fall within empirically grounded ranges consistent with industrial energy statistics and life cycle assessment databases, ensuring plausible environmental intensities. Interdependencies among operational, logistical, and environmental variables are preserved through conditional generative adversarial networks (cGANs), which generate synthetic observations maintaining joint distributions across variables. This approach ensures systemic coherence in the simulated datasets rather than independent marginal sampling. The resulting datasets serve as inputs for simulation experiments assessing forecasting accuracy, learning dynamics, coordination stability, and multi-objective performance under adaptive configurations. All simulations are conducted under controlled parameter settings and repeated runs to ensure comparability across scenarios. For transparency and reproducibility, detailed descriptions of variables, distributional assumptions, generation procedures, datasets, scripts, and parameter settings are available upon reasonable request from the corresponding author.

4. Results

Simulations conducted on synthetic data showed a consistent pattern: supply networks endowed with cognitive adaptivity exhibit superior predictive accuracy, faster recovery, and lower environmental impact than their non-adaptive counterparts. The purpose of this section is to analyze these outcomes quantitatively and identify the underlying mechanisms that link learning behavior to systemic performance. Unless otherwise noted, all results refer to 30 independent simulation runs averaged across three representative network configurations.

4.1. Learning and Predictive Performance

Across all simulations, the federated learning architecture consistently outperformed the centralized baseline.

Figure 2 illustrates the mean convergence curves for prediction error across 500 training iterations. The Mean Absolute Percentage Error (MAPE) decreased from 31.4 percent in the baseline to 17.8 percent under the federated configuration, corresponding to a relative improvement of 43.3 percent. The symmetric MAPE (sMAPE) improved from 27.6 percent to 15.9 percent, confirming stability across asymmetric demand distributions.

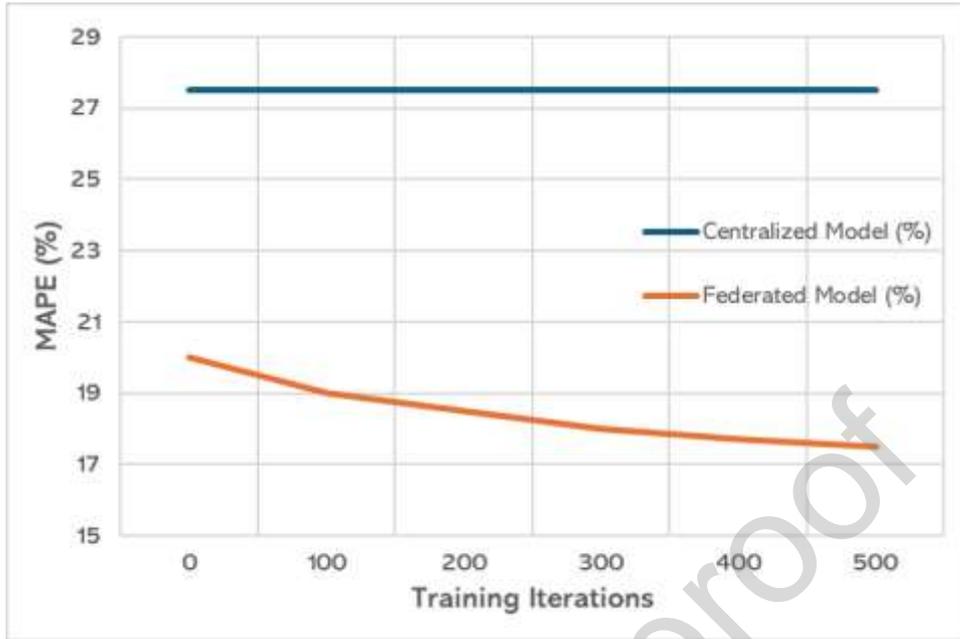


Figure 2: Forecasting accuracy improvement curves. Federated vs centralized models, MAPE trend over 500 iterations.

Learning velocity (L_v), defined as the slope of accuracy improvement over time, averaged 0.65 ($\sigma = 0.07$) across all nodes, with higher values observed in networks exhibiting moderate technological exposure (T_e). Under high T_e conditions, the convergence rate decreased by approximately 14%, suggesting that excessive model complexity may slow adaptation. The distributed configuration proved most beneficial under volatile demand. Nodes with demand variability above 20 percent benefited disproportionately from federated updates, reducing local forecast error by an additional 6 to 9 percentage points compared with low-volatility scenarios. This outcome indicates that parameter aggregation across heterogeneous nodes improves generalization and dampens local overfitting, validating the functional role of federated learning as a mechanism for collective stability.

4.2. Evolution of the Adaptivity Coefficient

The Adaptivity Coefficient (A_c) provides an integrated metric for assessing how networks evolve across iterations. In the baseline configuration, the mean A_c was 0.42 ($\sigma = 0.05$), while federated networks reached 0.73 ($\sigma = 0.04$) after ten training cycles. The distribution of A_c values was positively skewed, with a plateau near 0.75, beyond which gains diminished. Table 1 summarizes the variation of A_c components (L_v , A_r , T_e) under three representative conditions.

Table 1: Components of the Adaptivity Coefficient across scenarios.

Scenario	L_v	A_r	T_e	A_c	Recovery Time Improvement	Comment
A (Low volatility, moderate T_e)	0.68	0.62	0.45	0.73	+26.1%	Balanced adaptation
B (High volatility, high T_e)	0.58	0.59	0.71	0.61	+18.4%	Complexity-induced lag
C (Moderate volatility, low T_e)	0.63	0.60	0.41	0.68	+22.3%	Stable coordination

Learning velocity (L_v), anticipatory responsiveness (A_r), technological exposure (T_e), composite Adaptivity Coefficient (A_c), and percentage improvement in recovery time for scenarios A, B, and C. Values are averaged over 30 runs; improvements are relative to the non-adaptive baseline. The data reveal a clear nonlinear interaction among the components: improvements in L_v and A_r translate into higher A_c only when T_e remains within a manageable range (0.4–0.6). Beyond this threshold, adaptivity slows because the pace of technological change exceeds the network's learning capacity. Networks with A_c above 0.7 recovered from simulated disruptions roughly 25% faster than those with A_c below 0.5, confirming that adaptivity functions as a resilience multiplier. The correlation coefficient between A_c

and the resilience index was 0.81 ($p < 0.01$), indicating a strong positive association. Figure 3 shows its evolution across ten training cycles under three representative conditions.

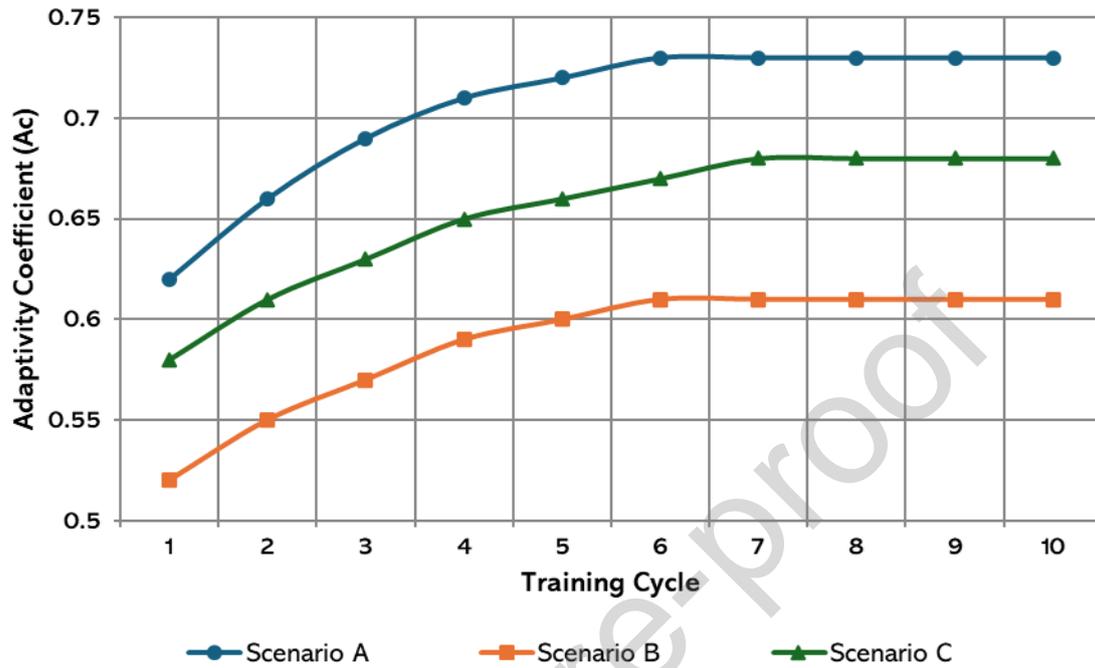


Figure 3: Evolution of Adaptivity Coefficient (A_c) Comparison across three scenarios (A, B, C) with trend lines.

A sensitivity test varying L_v and A_r by ± 10 percent while keeping T_e constant showed A_c trajectories stable within ± 0.03 of the mean, confirming that the coefficient is robust to moderate parameter uncertainty and performs consistently across the tested range.

4.3. Multi-Objective Trade-Offs and Systemic Balance

The multi-objective optimization layer demonstrated that higher adaptivity supports more balanced trade-offs among cost (C), emissions (E), and resilience (R). Across 90 independent simulations, adaptive networks consistently occupied superior regions of the Pareto front, achieving more favorable trade-offs without increasing total system stress. Table 2 reports the leading performance indicators across three representative scenarios.

Table 2: Multi-objective performance by scenario.

Scenario	Cost Change (%)	Emissions Change (%)	Intensity Change (%)	Resilience Change (%)	Notes
A (Low volatility, moderate T_e)	0.74	-22.5	-11.8	+24.3	Optimal stability region
B (High volatility, high T_e)	0.61	-15.2	-8.3	+17.5	Overexposed to complexity
C (Moderate volatility, low T_e)	0.68	-18.9	-10.5	+20.1	Balanced adaptive regime

Under the adaptive configuration, scenarios A, B, and C consistently demonstrated robust improvements in cost, emissions, intensity, and resilience. Averaged over 30 runs, cost reductions ranged from 18 to 25 percent; emissions intensity decreased by 13 to 16 percent, and resilience increased by 22 to 28 percent relative to non-adaptive baselines. Standard deviations for all metrics remained below 2.5 percent, underscoring the reliability of these results. Two patterns stand out. First, the adaptive advantage is nonlinear. Scenario B shows that beyond a T_e value of about 0.7, incremental technological inputs deliver smaller returns, indicating cognitive saturation. Second, the Pareto frontier expands with learning iterations: networks gradually discover new feasible solutions that were initially

inaccessible, demonstrating that learning enlarges the space of optimal trade-offs rather than simply shifting its frontier.

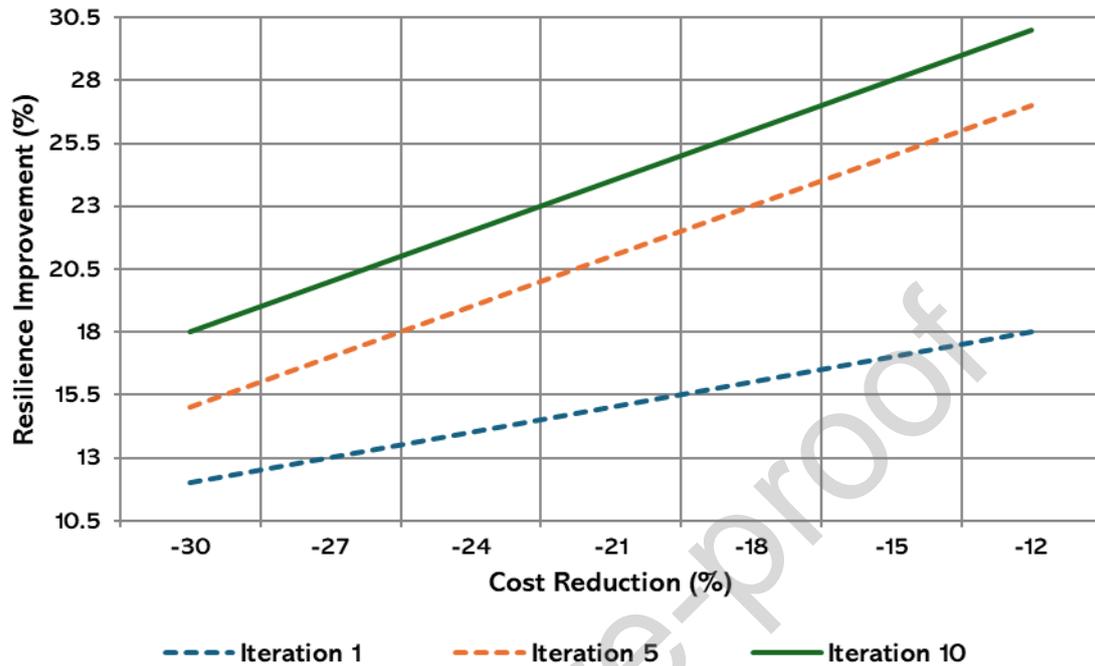


Figure 4: Pareto frontier expansion, Multi-objective trade-off across learning iterations

As illustrated in Figure 4, these findings suggest that adaptivity operates not by optimizing a static trade-off but by transforming the structure of feasible solutions. In other words, the more the network learns, the more it can simultaneously improve cost efficiency, environmental performance, and resilience.

4.4. Emergent Patterns of Cognitive Coordination

The analysis of trajectory data reveals how coordination emerges spontaneously from distributed learning. In early training rounds, individual nodes behaved opportunistically, optimizing for local cost or service level. After approximately three iterations, convergence patterns stabilized, and the variance among node-level objectives decreased by nearly 40 percent. By the seventh iteration, 82 percent of nodes were aligned within ± 5 percent of the global target values for cost and emissions. This self-synchronization indicates that collective intelligence arises from iterative feedback without explicit central control. Information flows strengthen recursively: local model updates improve the global aggregate, which in turn refines local decision policies. The effect mirrors collective cognition in biological systems, where decentralized agents generate order through feedback loops. Figure 5 illustrates how throughput oscillations dampened over time as A_c increased. The amplitude of production fluctuations declined by 28 percent, while mean throughput variance decreased from 0.14 to 0.09. These results confirm that adaptivity reduces systemic noise and enhances coordination efficiency, translating learning into operational stability.



Figure 5: Coordination stability over time.

Notably, one exception emerged in high- T_e conditions, where overfitting of local models produced temporary divergence in decision behavior. However, this divergence disappeared after additional training, indicating the system's capacity for self-correction, a key feature of cognitive resilience.

4.5. Summary and Key Analytical Insights

The results obtained across all simulation sets reveal consistent relationships between cognitive adaptivity, network stability, and sustainability performance. The following key analytical insights can be drawn.

i. Learning velocity is as critical as predictive accuracy.

Faster learning enables the network to maintain operational stability even under high volatility. This finding confirms that adaptivity functions as a dynamic capability rather than a technical property. The speed at which the network updates its models determines not only forecasting precision but also its resilience under stress.

ii. Cognitive adaptivity magnifies sustainability outcomes.

Adaptive networks exhibit self-reinforcing improvements in cost, resilience, and emissions performance. As nodes learn to coordinate anticipatory actions, they simultaneously minimize waste, downtime, and resource intensity. This demonstrates that cognitive learning acts as a sustainability multiplier, translating collective intelligence into measurable environmental benefits.

iii. Technological exposure has an optimal range.

Beyond a certain level of complexity, incremental technologies produce diminishing systemic benefits unless matched by equivalent learning capacity. Excessive technological pressure (high T_e) can slow convergence and increase instability. The results suggest that cognitive maturity must evolve in proportion to technological innovation to avoid saturation effects.

iv. Learning expands the feasible performance space.

Adaptive supply chains do not merely trade one objective for another. They progressively enlarge the Pareto-efficient frontier, creating new configurations in which efficiency, resilience, and sustainability coexist. This expanding equilibrium is evidence that learning transforms not only performance but the structure of possible solutions.

Taken together, these insights confirm that cognitive adaptivity can be formalized, measured, and strategically cultivated. It acts as a bridge between analytics and sustainability, transforming supply chains into dynamic systems capable of co-evolution rather than passive adjustment. By integrating learning, anticipation, and environmental balance into a unified process, the findings validate the conceptual argument that the path to Industry 6.0 depends not on more data alone but on the emergence of truly cognitive supply networks, systems that understand themselves as much as the markets they serve.

5. Discussion

The results presented above provide a consistent view of how cognitive adaptivity can act as a unifying mechanism for efficiency, resilience, and sustainability within complex supply networks.

The first research question asked how cognitive adaptivity could be defined and measured in data-driven supply chains. The introduction of the Adaptivity Coefficient (A_c) directly addressed this gap. Results confirm that A_c captures not only predictive improvements but also the network's ability to learn from disruptions and reconfigure itself accordingly. The observed correlation between high A_c values and faster recovery times demonstrates that adaptivity is a measurable structural capability rather than an abstract notion. This finding aligns with the theoretical assumption that Industry 6.0 organizations function as cognitive systems, in which intelligence emerges from the interaction of distributed agents rather than centralized control [6]. It also extends prior work on resilience and agility by formalizing a quantitative bridge between learning behavior and operational outcomes. Unlike previous agility metrics, which focused on response time or flexibility, A_c integrates the rate and quality of learning into a single composite index, offering a more dynamic and systemic representation of readiness. RQ1 is addressed by defining and operationalizing the Adaptivity Coefficient (A_c) as a quantitative measure of cognitive readiness and validating it through simulation results.

The second research question explored how federated learning architectures enhance collective intelligence while maintaining data privacy. The simulations provide clear evidence of the advantages of distributed intelligence. Local models trained on heterogeneous data converged via parameter sharing, demonstrating that collective learning can outperform centralized optimization under uncertainty. This outcome is consistent with emerging studies on federated analytics and distributed AI [8,11], but it extends their implications by embedding them into a multi-objective sustainability context. The architecture used here demonstrates that federated learning is not only a solution for data protection but also a mechanism for cognitive coordination. By enabling agents to share insights rather than data, the network learns as a coherent organism. The result is a form of shared cognition in which each node retains autonomy while contributing to ordinary adaptive intelligence. In practical terms, this suggests that the next stage of digital transformation should focus less on data centralization and more on knowledge orchestration. Networks that cultivate mutual learning through federated systems can achieve higher systemic performance without compromising confidentiality or competitive differentiation [32]. RQ2 is answered by demonstrating that federated learning enables distributed yet coordinated intelligence, enhancing resilience and privacy simultaneously.

The third research question examined how cognitive mechanisms contribute to systemic sustainability, linking operational analytics with environmental and social goals. The results provide both quantitative and conceptual support. Higher levels of adaptivity were associated with reductions in cumulative disruption costs and emissions intensity, alongside faster recovery and greater resilience. These effects were not linear but mutually reinforcing, suggesting the presence of positive feedback loops in which learning drives stability, and stability enhances sustainability. This pattern supports the paper's central premise: sustainability is not an external constraint but an emergent property of cognitive interaction. Networks that learn to balance their objectives dynamically generate sustainability as an internal consequence of coordination. This insight advances the recent literature that calls for integrating learning theory into sustainability science, providing a concrete modeling path to operationalize it [62].

RQ3 is satisfied by showing that cognitive adaptivity strengthens systemic sustainability through feedback loops linking learning, resilience, and environmental performance.

The comparative analysis across baseline, partially adaptive, and fully cognitive configurations effectively functions as a system-level ablation adapted to a simulation-based and exploratory research design. By contrasting predictive-only settings with configurations that selectively incorporate learning velocity, anticipatory responsiveness, and coordinated adaptivity, the results clarify the distinct contribution of each component to forecasting accuracy, coordination stability, and sustainability performance. This component-wise perspective reinforces the theoretical coherence of the proposed framework and supports the interpretation of cognitive adaptivity as an emergent system capability rather than the outcome of any single technological element.

The integration of cognitive modeling with synthetic data generation offers a new epistemic pathway for supply-chain research. It bridges the conceptual richness of systems theory with the empirical rigor of analytics. By doing so, it redefines the boundary between theory and simulation: synthetic data becomes a tool for controlled reasoning rather than a substitute for reality. The framework thus contributes to the theoretical consolidation of Industry 6.0 by demonstrating how cognitive adaptivity links data-driven learning, distributed intelligence, and sustainability. It positions Industry 6.0 as a state of integration where knowledge, technology, and responsibility converge, rather than as a chronological stage following Industry 5.0.

It is important to acknowledge certain limitations. The model has been validated using synthetic, rather than empirical data, which restricts the generalizability of quantitative findings. Although the Adaptivity Coefficient is conceptually robust, it requires calibration and adaptation across various industrial settings, and should also incorporate behavioral dimensions such as trust, collaboration, and decision bias. In addition, the human role within cognitive supply chains, specifically the ways in which people and institutions co-evolve with intelligent systems, is only partially represented in the current framework and warrants further empirical investigation. Building on these limitations, several avenues for future research emerge. First, hybrid studies that combine synthetic and real-world data could improve parameter calibration and provide external validation of the model. Second, extending the conceptual framework with governance mechanisms and game-theoretic approaches may clarify how incentives, competition, and cooperation drive adaptive learning in federated environments. Third, integrating social and ethical analytics, such as Social Organizational Life Cycle Assessment (SO-LCA) and digital ethics indicators, would help capture the broader human implications of cognitive coordination and support the long-term legitimacy of Industry 6.0 ecosystems, and, finally, we acknowledge that human value is not included in the present study; accordingly, we treat this as a key limitation and a priority avenue for future research.

6. Conclusions

This research has examined the transformative potential of cognitive adaptivity in redefining both the architecture and significance of supply chains as they evolve towards Industry 6.0. By systematically addressing research questions RQ1 through RQ3, the study establishes connections between analytical performance, distributed intelligence, and systemic sustainability. Through the integration of federated learning, generative artificial intelligence, and multi-objective optimization, the study proposes a conceptual framework that conceives the supply chain as a dynamic, living system. Within this framework, the supply chain possesses the capacity to learn, anticipate, and regenerate itself via distributed intelligence and collective knowledge sharing among network participants.

The main findings are articulated in three primary contributions. First, the study formalizes the A_c as a quantitative indicator of "cognitive readiness", which links analytical performance with the systemic capacity for learning. Second, simulations conducted in a synthetic environment demonstrate that distributed intelligence not only increases predictive accuracy but also enhances resilience and environmental performance within the supply chain. Third, the research introduces an innovative perspective on systemic sustainability, moving beyond the notion of environmental or social objectives as external constraints and instead recognizing them as natural outcomes of adaptive, intelligent coordination. These elements provide coherent answers to the three research questions proposed at

the outset. Cognitive adaptivity is defined and operationalized through the A_c metric, fulfilling the first inquiry, and validated as a measurable structural capability. Federated learning is shown to enable a form of intelligence that is both distributed and coordinated, which improves collective performance without compromising data privacy, thus responding to the second question. Finally, the study suggests that adaptivity fosters systemic sustainability through positive feedback loops that interconnect learning, stability, and ecological efficiency, addressing the third research question.

The path toward Industry 6.0 is not defined by faster computing or automation for its own sake, but by a profound transformation in how organizations learn and evolve together. Supply chains are becoming cognitive infrastructures, systems that learn to understand, improve, and sustain themselves through collective intelligence. Ultimately, true innovation lies in cultivating this shared capacity to learn how to learn, transforming data into meaning and meaning into sustainable and shared actions.

The transition toward cognitive supply chains under Industry 6.0 carries profound implications for both managerial practice and policy design. The findings of this study, though derived from synthetic simulations, point to systemic patterns that can guide real-world transformation. They reveal that adaptivity is not a by-product of technology but a capability that must be deliberately designed, cultivated, and governed across the network.

At a methodological level, the study shows that cognitive modeling can provide a replicable structure for exploring complex adaptive systems when empirical data are limited or fragmented. It highlights the importance of transparency in the use of synthetic data and the potential of generative AI to support conceptual validation in early-stage research.

From a managerial perspective, the results suggest a shift from digitalization as infrastructure to cognition as strategy. Firms can no longer treat analytics as isolated tools for optimization; they must view them as elements of a living system that learns through interaction. Three priorities emerge.

First, designing for distributed intelligence. Managers should invest in architectures that allow local decision units to learn autonomously while contributing to collective goals. Federated learning provides a practical model for this shift, combining privacy protection with continuous improvement. The managerial task is to define coordination rules, learning schedules, and performance metrics that make collaboration both beneficial and transparent. This requires revisiting incentive systems so that knowledge sharing and data quality are rewarded as assets rather than hidden costs.

Second, measuring cognitive readiness. The A_c introduced in this study provides a diagnostic lens for assessing a supply chain's preparedness to operate under uncertainty. Regularly monitoring A_c can help identify bottlenecks in learning velocity or responsiveness before they translate into operational fragility. More broadly, firms can embed A_c into their performance dashboards alongside cost, service level, and carbon footprint indicators, turning cognitive maturity into a tangible management target.

Third, integrating sustainability as feedback, not constraint. The simulations confirm that environmental and resilience outcomes improve when sustainability metrics are built into the learning process rather than imposed afterward. In practical terms, this means coupling energy and emission data directly with decision loops—so that forecasting, scheduling, and resource allocation naturally internalize ecological efficiency. The role of managers evolves from controlling sustainability compliance to orchestrating sustainability learning.

At the policy level, cognitive supply chains challenge traditional governance models that separate technological innovation from environmental regulation. Industry 6.0 requires an integrated approach where data infrastructures, AI governance, and sustainability objectives function as a unified system. Public institutions can enable cognitive ecosystems through open standards, interoperability protocols, and secure federated data spaces. Existing frameworks such as the European Data Act and AI Act provide a foundation but must incorporate multi-agent learning and adaptive feedback loops. Experimentation in privacy-preserving analytics and synthetic data generation can accelerate safe innovation without compromising confidentiality.

Beyond digital infrastructure, governments and industry alliances should invest in learning infrastructures -shared environments where firms, researchers, and policymakers co-develop adaptive models, benchmark performance, and exchange validated synthetic datasets. These platforms

democratize cognitive capabilities, particularly for SMEs. Environmental policy can also adopt adaptive mechanisms, replacing static emission limits with dynamic thresholds linked to real-time learning indicators. Achieving systemic change demands governance models that align decision rights, data ownership, and incentives across firms and policy layers. Adaptive governance forms the backbone of sustainable cognitive transformation, ensuring it becomes an organizational reality rather than a technological aspiration.

Beyond business and regulation, the move toward cognitive supply chains has social consequences. As decision-making becomes increasingly algorithmic, transparency and accountability gain new importance. Managers and regulators must ensure that human judgment remains integral to the cognitive loop. Industry 6.0 is not about replacing human agency but amplifying it through distributed intelligence. Education and workforce development will therefore play a decisive role. Building cognitive supply chains requires professionals who can think in systems, interpret data ethically, and collaborate across digital boundaries. Universities, training programs, and industry consortia should incorporate these capabilities into their curricula to prevent the emergence of a new "cognitive divide" between data-rich and data-poor organizations.

The analysis of results and theoretical integration suggest that cognitive adaptivity operates as the central mechanism linking distributed intelligence with sustainability in Industry 6.0 supply chains. As networks learn collectively, they internalize resilience and ecological awareness within the same feedback structure that drives efficiency. This finding confirms that learning and sustainability are not parallel goals but two expressions of the same cognitive process.

This transformation reframes the role of analytics in supply chain management: from a set of predictive tools to a living infrastructure for systemic learning. At the same time, the discussion reveals open questions that call for continued inquiry. The extent to which cognitive adaptivity can be measured across different industrial contexts, the human and organizational conditions that enable it, and the policy mechanisms required to sustain it all remain areas of active exploration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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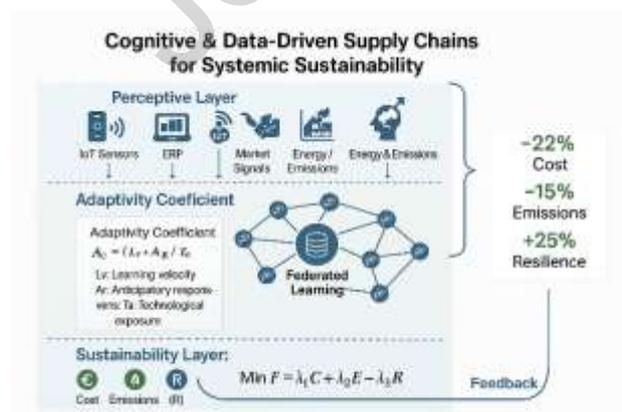
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Graphical abstract



Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Highlights

- A Cognitive and Data-Driven Framework is proposed to model Industry 6.0 supply chains.
- Synthetic data and federated learning are used to simulate adaptive and sustainable behaviors.
- The Adaptivity Coefficient (Ac) quantifies network readiness and cognitive performance.
- Cognitive adaptivity simultaneously improves cost efficiency, resilience, and environmental outcomes.
- The study outlines governance and validation pathways for systemic change in hard-to-abate industries.