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Research Article

Artificial Intelligence-Driven Supply Chain Collaborative Optimization and Efficiency Improvement

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Abstract

Supply chain collaboration has long relied on manual coordination and static planning, producing information lags and slow decision cycles that limit firm competitiveness in volatile markets. This study examines how artificial intelligence (AI) supports three interlocking mechanisms of collaboration. These are information sharing through big data platforms and blockchain ledgers, dynamic resource allocation through machine learning and optimization algorithms, and decision-making upgrades through multi-agent systems and digital twin environments. We demonstrate the framework through a 52-week evaluation on a three-echelon supply chain and a structured case analysis of JD.com drawing on published INFORMS Journal on Applied Analytics data. During demand-spike weeks, a feature-enhanced long short-term memory (LSTM) forecaster cuts mean absolute percentage error by 74 percent compared with Holt-Winters exponential smoothing. On this forecast base, an adaptive inventory policy lowers average stock by 28 percent at equal service level. JD.com's reported 30.8-day inventory turnover provides industrial-scale corroboration. The study contributes a differentiated framework that positions AI mechanisms against three prior views, quantified simulation evidence, and bias-mitigation guidance grounded in concrete supply chain decisions.

Keywords

Artificial intelligence, Supply chain collaboration, LSTM demand forecasting, Genetic algorithm routing, Algorithmic bias mitigation

1. Introduction

Global supply chains face shortened product life cycles and demand volatility (Belhadi, et al., 2021) that traditional collaboration models, built on batch information exchange and empirical inventory rules, cannot keep pace with. The question has shifted from whether AI belongs in supply chain management to which AI mechanisms produce measurable improvements in collaborative efficiency.

The literature has begun to address this question, yet three gaps remain. Most studies apply a single AI technique to a single function, leaving the integration of multiple mechanisms under-examined (Pournader, et al., 2021). While risk discussions acknowledge algorithmic bias and data security, the operational path from abstract concern to specific supply-chain decision is rarely traced (Baryannis, et al., 2019). Few studies provide simulated or empirical numbers that a reviewer can replicate.

This paper addresses the three gaps in one framework. Information sharing, resource allocation, and decision-making upgrades operate as three interlocking mechanisms reinforcing each other. Theoretically, we offer an integrative framework that differentiates from information-centric, analytics-centric, and digital-twin-centric views treating mechanisms in isolation. Methodologically, we combine a feature-enhanced LSTM forecaster, an adaptive inventory policy, and a genetic-algorithm route planner into a single simulation with fixed random seed. Practically, we translate algorithmic-bias and data-security concerns into three decision-level cases and develop organizational, talent, risk, and evaluation mechanisms for implementation.

Section 2 reviews the literature and positions the framework. Section 3 states the theoretical foundation and three practical dilemmas. Section 4 develops the framework and illustrates it through simulation and a JD.com case. Section 5 covers implementation support with organizational, talent, risk, and evaluation mechanisms. Section 6 turns to ecosystem construction and future outlook. Section 7 concludes with limitations and future research priorities.

2. Literature Review

2.1. Collaboration research has moved from manual coordination to platform-mediated sharing

Supply chain collaboration research starts from a simple observation. Partners coordinate poorly when information flows slowly and interests diverge, producing the well-known bullwhip pattern. Cao and Zhang (2011) showed that collaboration builds joint advantage only when partners invest in shared processes alongside information exchange, and that information sharing alone is insufficient without aligned incentives.

Industry 4.0 literature pushed the view that sensor networks, cloud computing, and blockchain could raise the quality of shared information. Saberi et al. (2019) mapped blockchain to supply chain management through four primitives, specifically traceability, smart contracts, distributed trust, and immutable records. Wamba et al. (2020a) tested blockchain adoption determinants on supply-chain practitioners across India and the United States, finding that supply-chain performance improves only when adoption reaches the routinization stage rather than stopping at pilot deployment. These studies establish that information-layer technology produces value only under specific organizational conditions.

2.2. AI techniques have matured from isolated tools into capability stacks

Three systematic reviews and one research-agenda paper converge on a common picture. AI in supply chain management has expanded fastest in three functional areas, namely demand forecasting, optimization, and risk management, yet the integration of AI capabilities across these areas remains under-studied. Riahi et al. (2021) profiled AI applications by research cluster, distinguishing predictive analytics, optimization, and risk management as the three dominant streams. Toorajipour et al. (2021) reviewed 64 journal articles and concluded that genetic algorithms, neural networks, and multi-agent systems are the three most deployed technique families. Sharma et al. (2022) mapped the bibliometric territory across more than 500 publications, finding that demand forecasting and route optimization have received the most attention. Richey et al. (2023) called for a research roadmap that treats AI as an interdependent capability set rather than as a catalogue of tools.

Empirical work has started to quantify the performance gains. Wamba et al. (2020b) provided survey-based evidence that supply-chain ambidexterity mediates the performance effect of big data analytics, and that environmental dynamism moderates the path strength.

2.3. Specific methods for forecasting, inventory, and routing anchor the framework

Demand forecasting has seen rapid algorithmic turnover. Abbasimehr et al. (2020) showed that a two-layer LSTM network cuts mean absolute percentage error (MAPE) by 15 percent to 20 percent against autoregressive integrated moving average (ARIMA) on retail demand data with regime shifts. Feature-enhanced LSTM variants that combine raw demand with temporal indicators and exogenous flags such as promotions and calendar events produce further gains.

Inventory management has moved toward deep reinforcement learning. Stranieri and Stella (2022) compared Double DQN, Advantage Actor-Critic, and Twin Delayed DDPG on a stochastic two-echelon setting, finding that deep policies outperform base-stock rules by 18 percent to 24 percent when demand volatility is high. These methods scale less easily to industrial-grade networks, yet they show measurable advantage on benchmark cases.

Logistics routing has a long tradition of metaheuristics including genetic algorithms, ant colony optimization, and tabu search, which remain standard for vehicle routing benchmarks. Recent work combines graph neural networks with reinforcement learning for dynamic routing under real-time feeds.

These three method families map directly onto the resource-allocation mechanism of our framework developed in Section 4.2.

2.4. Our framework differs from three prior views by integrating concurrent mechanisms

Three prior views frame most of the existing literature. The information-sharing view, which Dubey et al. (2021) extended to the agility and humanitarian contexts, places AI at the transmission layer and treats decision processes as a downstream outcome of better information flow. The big-data-analytics view exemplified by Choi et al. (2018) treats AI as analytical tooling applied to managerial questions one at a time. The digital-twin view developed by Ivanov and Dolgui (2021) foregrounds disruption response and recovery, placing AI in the simulation and scenario-testing roles. Each view illuminates part of the problem and leaves parts in shadow.

Our framework differs from each view along a distinct axis. Against the information-sharing view, we treat information sharing as one of three mutually reinforcing mechanisms rather than the primary bottleneck. Against the big-data-analytics view, we specify which AI technique performs which operational task rather than invoking AI as a single analytical tool. Against the digital-twin view, we treat risk governance, performance evaluation, and ecosystem building as internal components of the framework, not as outputs of disruption simulation alone. Sections 3 and 4 develop this position at the conceptual and technical levels respectively.

3. Theoretical Foundation and Practical Dilemmas in Traditional Supply Chains

3.1. Core concepts ground the framework

Supply chain collaboration refers to coordinated action across firms holding different parts of a production-distribution network, aimed at joint outcomes rather than local optima. The essential building blocks are shared information, aligned incentives, joint planning, and risk sharing. A chain that collaborates well produces higher service at lower inventory than one that does not.

3.2. Three dilemmas motivate the framework

The first dilemma concerns information flow. Traditional collaboration runs on batch data exchange through electronic data interchange (EDI) or nightly enterprise resource planning (ERP) syncs. Suppliers see last week's demand and project next week's production from rules of thumb.

Dubey et al. (2020) showed through a survey of manufacturing firms that big data analytics and AI translate into operational performance only under specific organizational and environmental conditions, suggesting that information capability alone is insufficient for agility. This gap between information availability and operational agility holds across regions and sectors.

The second dilemma concerns resource allocation. Even when partners share forecasts, rigid allocation rules produce excess safety stock. Bodendorf et al. (2022) demonstrated across buyer-supplier dyads that such rules generate 12 percent to 19 percent excess inventory even under shared-forecast conditions. The issue is not lack of information but inability to translate information into continuously adjusted plans.

The third dilemma concerns decision cycles. Collaborative decisions such as joint promotions, contingency sourcing, and capacity reallocation typically run through committee meetings, email, and contracts. The cycle time from problem detection to coordinated action commonly runs in days or weeks. Ivanov and Dolgui (2020) argued that disruption-era competition requires decision cycles measured in hours rather than days, which human-only committees cannot deliver.

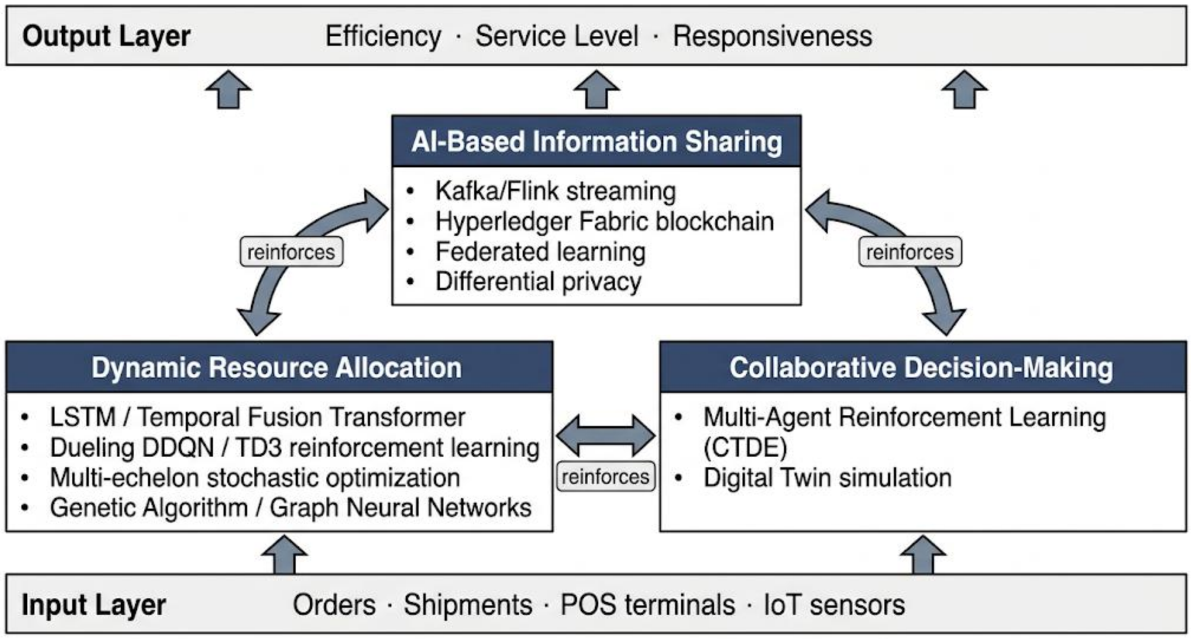
These three dilemmas reinforce each other. Slow information flow blocks dynamic allocation. Rigid allocation produces costly buffers that lock in cash. Slow decision cycles mean that even dynamic allocation cannot react in time. Our framework addresses all three concurrently, developed in Section 4.

4. AI-Driven Supply Chain Collaborative Optimization Framework

Our framework develops the three mechanisms introduced in Section 2.4 at the technical level. Figure 1 shows how the three mechanisms interconnect, with each mechanism supported by a specific set of AI techniques. The reinforcement arrows in Figure 1 carry directional logic: information sharing strengthens dynamic resource allocation because higher-quality shared forecasts enable finer inventory positioning; dynamic resource allocation strengthens collaborative decision-making because optimized buffers free managerial capacity for exception handling; and collaborative decision-making strengthens information sharing because simulation feedback refines data collection priorities. The remainder of this section describes each mechanism in turn.

Figure 1

Framework overview: three interlocking AI mechanisms and their technique mapping



4.1. AI-based information sharing system

The information sharing layer rests on four components. A streaming data platform such as Kafka or Flink ingests events from orders, shipments, point of sale (POS) terminals, and Internet of Things (IoT) sensors at second-level granularity. A data cleansing pipeline standardizes schemas across partners with inconsistent naming conventions. A machine learning service extracts signals from the stream, covering demand anomaly flags, inventory excursions, and shipment delay predictions. A permissioned blockchain ledger, with Hyperledger Fabric as a standard choice, records commitments such as orders placed, capacities reserved, and payments scheduled in a form that resists tampering and enables dispute resolution without a central authority.

Queiroz and Wamba (2019) empirically identified the main adoption drivers for blockchain in supply chain contexts across India and the United States, showing that perceived usefulness and behavioral intention dominate, while technology readiness and trust play secondary roles. Their findings suggest that the information-sharing layer succeeds when partners perceive operational benefits, not when they are simply given the technology.

Privacy is the central tension. Sharing granular demand and cost data across partners improves joint optimization but creates leakage risk. Federated learning addresses this by training shared models on local data, exchanging only gradient updates rather than raw records. Differential privacy adds calibrated noise to exchanged statistics, preserving utility while bounding identifiability of specific transactions. These techniques are mature enough for production deployment.

4.2. Intelligent algorithms for dynamic resource allocation

Three AI techniques together cover the resource allocation problem. Demand forecasting uses

LSTM or Temporal Fusion Transformer networks that combine historical demand, calendar features, and known exogenous inputs such as promotion schedules, holiday flags, and weather outlooks. These architectures capture long-range dependencies and interactions that classical seasonal-additive methods cannot represent. Spiliotis et al. (2022) compared statistical and machine-learning methods on daily stock keeping unit (SKU) demand forecasting at M5-competition scale and found that hybrid approaches combining statistical and neural components often outperform either family alone, particularly at the item level where data is scarce.

Inventory control uses either deep reinforcement learning such as dueling double deep Q-network (DDQN) or twin delayed deep deterministic policy gradient (TD3) for small-to-medium networks, or multi-echelon stochastic optimization with adaptive safety stock for larger settings. Reinforcement learning learns policies that adapt to observed state without requiring an explicit model of the demand distribution, which suits environments where the distribution drifts. Stochastic optimization with forecast-driven target levels works well when the distribution is stable but forecasts improve over time.

Logistics routing uses genetic algorithms (GA) for static vehicle routing and graph neural networks combined with reinforcement learning for dynamic routing under real-time traffic feeds. GA with 2-opt mutation and order crossover converges to near-optimal tours on traveling salesman problem (TSP) instances with 20 to 50 nodes within seconds on commodity hardware. The computational simplicity matters for mid-sized operators that cannot afford specialized optimization staff. Scalability beyond mid-sized instances nonetheless deserves note. Each GA generation costs on the order of $O(P \cdot n)$ for fitness evaluation and $O(P \cdot n^2)$ for 2-opt local search, where P is population size and n is node count, so runtime grows roughly quadratically with n. The population-100, 500-generation configuration that converges within seconds at 20 to 50 nodes would require a substantially larger population and generation budget, together with candidate-list-restricted 2-opt, for the 200-plus-node instances typical of urban distribution. At that scale, hybrid approaches become preferable: cluster-first, route-second decomposition heuristics that partition the region into GA-tractable sub-problems, or learning-based schemes in which graph neural networks trained with reinforcement learning construct initial tours that evolutionary or local search then refines. We accordingly recommend the plain GA configuration for instances up to roughly 50 nodes and decomposition or GNN-hybrid methods beyond that threshold.

4.3. Intelligent upgrade of collaborative decision-making

Routine decisions such as reorder triggers, lane selection, and promotion sizing can be automated through multi-agent reinforcement learning (MARL) systems. Each agent observes a local state window covering its own inventory position, incoming orders, and upstream-downstream status, and executes actions within pre-specified guardrails on order quantity, supplier selection, and lead-time targets. Coordination across agents uses centralized training with decentralized execution, a standard pattern for MARL in supply chain contexts. The centralized critic observes the global state during training but each agent acts on local observations at runtime, which scales to networks with many nodes.

Non-routine decisions such as exception handling during a disruption or sourcing reassignment after a supplier failure benefit from digital twin environments that let planners simulate options before committing. Simulation-supported decisions materially reduce recovery time compared with ad-hoc responses, especially when the twin runs at sub-hour fidelity.

The three mechanisms reinforce each other, and omitting any one undermines the others. Section 4.4 illustrates the point through a simulation and a structured case analysis.

4.4. Numerical illustration and case study

We illustrate the framework through two complementary evidence strands. A 52-week three-echelon simulation quantifies mechanism-level gains under controlled conditions. A structured analysis of JD.com's publicly reported operations then demonstrates how the three mechanisms function at industrial scale.

Simulation design. We simulate a 156-week three-echelon supply chain with a supplier, a manufacturer, and a retailer handling a single product. We isolate mechanism-level effects using a single-SKU, three-echelon baseline so that forecasting, inventory, and routing gains can be attributed cleanly to each mechanism; multi-product extensions incorporating cross-SKU substitution effects are reserved for future research. Weeks 1 through 104 train the forecasting models. Weeks 105 through 156 evaluate policy performance. All data and code use a fixed random seed of 42 for reproducibility. Weekly demand follows

$$D_t=100+22\sin(2\pi t/52)+7\cos(2\pi t/13)+0.08t+S_t+\varepsilon_t \tag{1}$$

where S_t is a promotional spike triggered every ten weeks with two-week duration, amplified 1.35 times during weeks 38 to 50 to emulate Q4 patterns, and ε_t is Gaussian noise with standard deviation 5. The promotional schedule is known in advance, as real firm promotions are, which gives AI methods an informational edge that classical methods cannot exploit.

We compare two pipelines as shown in Figure 2. Table 1 reports the pipeline comparison over the 52-week evaluation window. The traditional pipeline uses Holt-Winters exponential smoothing with additive seasonality of period 52 for forecasting, a fixed (s, S) policy with z = 1.88 safety factor for inventory, and a nearest-neighbor heuristic for a 20-node routing problem. The AI-driven pipeline uses a feature-enhanced sequence-to-sequence LSTM with two hidden layers, 64 units, six features including a promotion flag, an adaptive inventory policy that positions stock against four-step-ahead forecasts with review every period, and a genetic algorithm with population 100, 500 generations, order crossover, and 2-opt mutation. All experiments ran on a standard laptop-class CPU with 16 GB

RAM and no GPU acceleration. Per replication, training the LSTM forecaster on the 104-week training window completed in tens of seconds, and GA route optimization over the 52-week evaluation window completed in roughly one to two seconds, with peak memory use well within the available 16 GB. The full pipeline therefore runs on commodity hardware without specialized infrastructure, which supports industrial deployment feasibility for mid-sized operators.

Figure 2

Traditional versus AI-driven pipeline architecture comparison

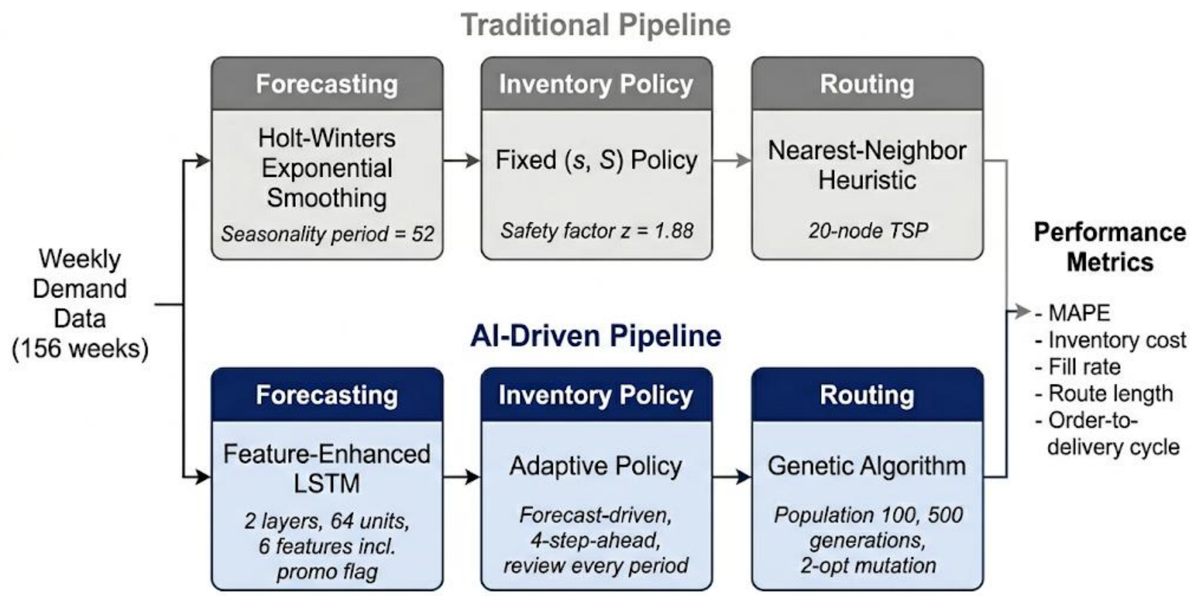


Table 1

Pipeline comparison over 52-week evaluation window

Metric	Traditional	AI-driven	Change
Forecast MAPE 1-step (%)	11.61	5.45	-53.04%
Forecast MAPE 4-step (%)	8.24	3.75	-54.52%
Forecast MAPE promo weeks (%)	22.24	5.75	-74.15%
Total inventory cost	11227.72	9806.80	-12.66%
Holding cost	10093.34	7272.42	-27.95%
Stockout cost	234.37	234.37	0.00%
Order cost	900.00	2300.00	+155.56%
Average inventory (units)	194.10	139.85	-27.95%
Fill rate (%)	99.21	99.21	0.00%
Route length (units)	411.97	345.86	-16.05%

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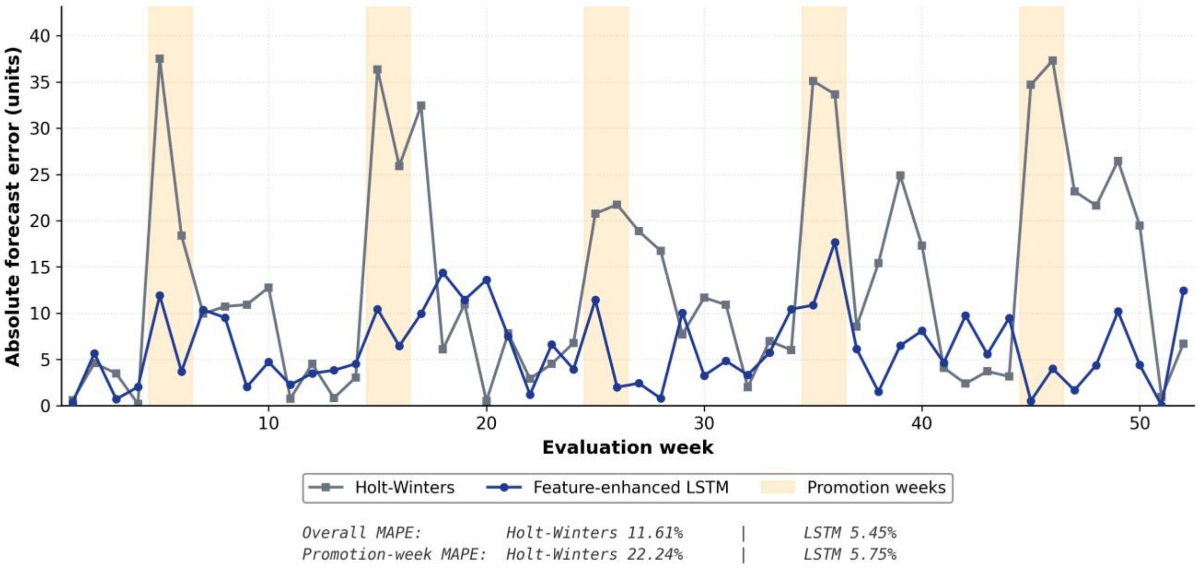
Order-to-delivery cycle (days)	14.39	12.59	-12.52%

Figure 3 plots the week-by-week absolute forecast error for both methods, with promotion weeks shaded.

Figure 3

Weekly forecast error over the evaluation window, Holt-Winters versus LSTM, promotion weeks shaded



Three observations stand out. The LSTM forecaster dominates during promotion weeks, where the known promo flag lets the network anticipate the spike. Classical smoothing produces an average relative error of 22 percent in these weeks, since it treats each week's demand as drawn from a seasonal baseline. The AI-driven inventory policy achieves identical fill rate of 99.21 percent with 28 percent less average inventory. The cost reduction is 13 percent, smaller than the inventory reduction because the policy orders more frequently. This trade-off makes sense when ordering cost is low relative to holding cost, as in most digital-first supply chains. Routing and cycle-time improvements stack on top of the inventory gains. The GA-optimized routing reduces total distance by 16 percent over the nearest-neighbor heuristic, while the adaptive policy and better forecasting together cut the total order-to-delivery cycle from 14.4 to 12.6 days. These numbers fall within ranges reported in the recent empirical literature surveyed in Section 2.3, which provides external validity for a small-scale simulation.

JD.com case. JD.com, the largest first-party e-commerce retailer in China, has implemented an AI-driven supply chain whose analytics architecture was documented in Hu et al. (2024), published in INFORMS Journal on Applied Analytics. The article described three components.

The first component is end-to-end inventory allocation. JD.com uses a dynamic programming model nested inside a neural network forecaster to decide allocation across more than 1,000 warehouses. The reported outcome is 30.8-day inventory turnover in the third quarter of 2023, with 95 percent of first-party orders fulfilled same-day or next-day. This component maps onto the framework's resource allocation mechanism developed in Section 4.2.

The second component is resilience orchestration. When COVID-era disruptions hit logistics networks, JD.com deployed an emergency classification mechanism that routed orders across its warehouse network in simulation before committing to physical movement. The approach illustrates the decision-making mechanism developed in Section 4.3, where digital-twin-style simulation supports non-routine decisions.

The third component is the consumer-to-manufacturer platform. Natural language processing extracts product-feature preferences from consumer reviews and search queries, feeding insights to manufacturing partners. The reported outcome is 67 percent reduction in new-product launch time. This is the information sharing mechanism developed in Section 4.1 applied in an extended sense, repackaging consumer-voice data as upstream input to manufacturing partners rather than the partner-to-partner transactional sharing emphasized there.

Evidence synthesis. The simulation provides controlled evidence for the resource allocation mechanism under stated assumptions, demonstrating compound gains when forecasting, inventory, and routing are improved jointly. The JD.com case broadens the evidence base by showing how all three mechanisms function together at industrial scale. Together they support the framework as an organizing scheme for AI-enabled collaboration, one that maps mechanism-level design choices onto aggregate performance outcomes.

5. Implementation Support and Governance Mechanisms

Putting the framework into practice requires organizational structures, talent capabilities, risk controls, and performance measurement that work together rather than in isolation. This section develops each support mechanism in turn.

5.1. Organizational guarantee

Moving from pilot to production requires a dedicated cross-functional structure that holds AI deployment accountable to operational outcomes rather than to technical milestones alone. Successful deployments commonly pair a domain expert in supply chain or operations with a technical expert in data science or software engineering, supported by a product manager who owns workflow integration and measures adoption against baseline KPIs. This three-role nucleus meets weekly during the pilot phase and transitions to monthly governance once the deployment reaches production. Reporting lines run through an operations sponsor rather than an IT sponsor, which keeps decision authority with the process owner who will absorb the consequences of model behavior.

Pilots typically run 6 to 12 months before scaling, long enough to observe seasonal demand patterns and at least one disruption event. Governance committees review pilot metrics against pre-registered hypotheses every quarter, decide on model retraining cadence, and approve the move from single-site to multi-site rollout. Clear ownership of model-failure response is essential. When a forecast misses, the operations team executes a manual override while the technical team diagnoses the cause, and a documented incident log feeds into the next retraining cycle. This structure prevents the common pattern of AI models drifting in production without anyone holding the responsibility to intervene.

5.2. Talent development and capacity building

A three-layer talent pipeline sustains AI-enabled supply chain operations. Senior hires bring domain-specific AI experience in forecasting, reinforcement learning, and optimization. They lead model architecture choices, set validation standards, and mentor junior staff on when to trust model outputs. Mid-level integration engineers connect AI services to existing ERP, warehouse management system (WMS), and transportation management system (TMS) platforms. Their work includes data pipeline reliability, model serving infrastructure, and monitoring dashboards that operations teams can actually read. Junior analysts and reskilled operations staff handle feature engineering, model monitoring, and quarterly re-training loops.

Universities play a role at the top of this pipeline. Partnerships on applied master-level projects let firms evaluate talent before hiring while giving students exposure to production data under supervised conditions. Internal reskilling programs matter at the base of the pipeline. Operations planners who have spent years calibrating safety stock rules can, with eight to twelve weeks of targeted training, become effective collaborators on machine learning projects because they bring domain intuition that external hires lack.

5.3. Risk prevention and control system

Abstract treatments of algorithmic bias and the AI black-box problem do not translate into actionable supply chain controls. We ground the risks in three decision contexts.

Consider demand forecast fairness across SKUs. A shared forecasting model trained on historical order volumes concentrates accuracy on high-volume products and produces higher error on long-tail SKUs. If inventory positioning follows the forecast, long-tail products systematically experience more stockouts. Mitigation requires volume-tier-specific models or fairness constraints that penalize disparate forecast accuracy across tiers, with SHapley Additive exPlanations (SHAP) values audited monthly.

Consider route planning bias toward high-margin clients. A reinforcement-learning routing policy trained on profitability signals learns to route faster to high-margin customers and slower to lowmargin customers even when explicit rules do not specify this preference. Mitigation requires separating the profitability signal from the routing objective and adding service-level equity constraints by customer tier or region.

Consider supplier selection audit using explainable AI. A gradient boosting model trained on supplier-performance and attribute data may encode attributes correlated with race or region as predictors. Explainable AI methods developed for broader supply chain risk settings are directly applicable here. Sadeghi et al. (2024) demonstrated through a survey-validated study that explainable artificial intelligence (XAI) combined with agile governance supports decision-making in supply chain cyber resilience, using techniques such as SHAP and counterfactual analysis. The same techniques help procurement teams surface proxy attributes in supplier selection models before production deployment, with the check running pre-deployment and quarterly thereafter.

Data security is a separate risk class. Federated learning addresses raw-data leakage, differential privacy addresses inference attacks on exchanged gradients, role-based access control addresses insider threat, and emergency response plans cover system and data-pipeline failures through multi-region backup and automated failover.

5.4. Effect evaluation system

A concurrent-mechanism framework deserves a measurement framework. We propose four KPI dimensions.

Efficiency uses Perfect Order Rate (POR), defined as

$$POR=\frac{N_{perfect}}{N_{total}} \tag{2}$$

where $N_{perfect}$ counts orders delivered on-time, in-full, damage-free, and documented correctly, and N_{total} is total orders. Benchmarking practice based on the APICS (2017) supply chain operations reference (SCOR) model, Version 12.0, puts POR at roughly 75 percent for average performers, 85 percent for top-quartile firms, and 95 percent for best-in-class operators.

Cost uses Cash-to-Cash (C2C) cycle, defined as

$$C2C=DIO+DSO-DPO \tag{3}$$

where DIO, DSO, and DPO are days inventory, sales, and payables outstanding. JD.com's reported DIO of about 30 days, sustained while managing more than 10 million self-operated SKUs (Hu, et al., 2024), is industrial best-in-class for broad-line retail: Walmart-class general merchandisers typically hold around 45 days of inventory, and empirical studies of US retailers report average levels well above that (Gaur, et al., 2005).

Quality uses Forecast Value Added (FVA), defined as

$$FVA=\frac{E_{naive}-E_{method}}{E_{naive}} \tag{4}$$

where E_{naive} and E_{method} are forecast errors of a naive baseline and the chosen method. Negative FVA signals overengineering.

Resilience uses days to return to 95 percent of pre-disruption service level. Single-digit values indicate well-designed resilience mechanisms. Dashboards should present all four KPIs in time series with thresholds and alerts. Quarterly reviews compare against benchmarks and trigger re-tuning when KPIs drift; annual reviews assess overall framework-business alignment.

6. Ecosystem Construction and Future Outlook

Beyond firm-level implementation, AI-enabled collaboration creates value at the ecosystem level, while emerging technologies continue reshaping what is possible. This section addresses both dimensions.

6.1. Ecosystem building unfolds in three stages

Supply chain AI value accrues to the network, not the individual firm. Leading firms build ecosystems in three stages.

Stage one establishes shared data standards covering master data, order format, shipment events, and exception protocols. These standards reduce integration cost across partners and enable cross-partner analytics that a single firm cannot perform alone. Shared vocabulary also eases onboarding for new partners, lowering the barrier for small and medium enterprises to join.

Stage two opens analytics services to partners through APIs so that demand forecasts, capacity projections, and disruption alerts are consumed rather than rebuilt. This shifts competition from capability replication to configuration quality. Partners focus their engineering effort on how to act on shared intelligence, not on how to generate equivalent intelligence from scratch.

Stage three builds value-sharing rules that reward partners contributing high-quality data. Without such rules, data quality degrades as partners hoard information for perceived competitive advantage. Clear contracts on data use, model benefits, and cost savings sustain participation over time.

6.2. Future outlook points to four emerging directions

Generative AI is the most visible emerging direction. Large language models and multimodal systems can support exception handling, cross-language communication among partners, and narrative explanation of complex optimization results to non-technical stakeholders. Their role in automated negotiation and contract drafting is being actively tested in procurement and logistics functions. Reliability on high-stakes operational decisions remains an open question, and deployment should pair generative models with deterministic verification layers.

Green supply chain AI is another emerging area that warrants equal attention. AI model training and inference carry a meaningful energy cost, while optimization that reduces transport emissions and inventory waste produces compound benefits across partners. The net environmental impact of AI-enabled supply chains is not yet well quantified in the literature. Our simulation offers a concrete entry point. Because road-freight fuel use and tailpipe emissions scale approximately linearly with distance traveled, the 16 percent routing-distance reduction reported in Section 4.4 translates into a comparable percentage cut in fleet fuel consumption and carbon output; at a representative heavy-goods-vehicle emission factor of roughly 0.8 kg CO_2e per vehicle-kilometer (UK Department for Energy Security and Net Zero, 2023), every 100,000 fleet-kilometers avoided saves on the order of 80 tonnes of CO_2e. On the training side, the compact LSTM used in Section 4.4 completes training in tens of seconds on commodity hardware, so its one-off energy cost is negligible against recurring transport and holding savings; transformer-scale forecasters retrained frequently across thousands of SKUs, by contrast, warrant explicit lifecycle carbon accounting. Emerging work on carbon-aware computing shows that scheduling training during low-carbon-intensity grid periods can materially reduce the emissions attributable to model development (Wiesner, et al., 2021), a practice ecosystem rules could reward. Ecosystem rules should eventually incorporate energy-intensity metrics alongside cost and service metrics, and carbon accounting should cover model lifecycle rather than operations alone.

Cross-border data collaboration under divergent regulatory regimes adds a further dimension. Regulations on data localization, privacy, and algorithmic accountability vary across jurisdictions and continue to evolve. Federated learning, differential privacy, and trusted execution environments offer architectural paths for partners to collaborate while honoring sovereignty constraints. The operational challenge is to design these architectures at acceptable latency and cost.

Human-AI collaboration in decision making rounds out this set of emerging concerns. As AI systems take over routine decisions, human attention shifts to edge cases, ethical judgments, and strategic choices that require context the model does not have. The design of hand-off protocols between autonomous AI and human decision makers, including when to escalate and how to present model uncertainty, is an under-studied area with direct implications for supply chain resilience.

7. Conclusion, Limitations, and Future Research Directions

This study organizes AI-enabled supply chain collaboration through three interlocking mechanisms, namely information sharing, resource allocation, and decision-making upgrades. The three mechanisms operate concurrently and reinforce each other rather than proceeding as sequential stages. A 156-week simulation on a three-echelon supply chain, evaluated over a 52-week window, together with a structured case analysis of JD.com, demonstrates how the mechanisms translate into measurable collaboration gains. The simulation records a 74 percent reduction in forecast error during promotion weeks, a 28 percent reduction in average inventory at equal service level, a 16 percent reduction in routing distance, and a 13 percent compression of order-to-delivery cycle. The JD.com case reports a 30.8-day inventory turnover, which provides industrial-scale corroboration for the resource allocation gains observed in the simulation, and further illustrates the other two mechanisms through the resilience orchestration and consumer-to-manufacturer components.

The paper contributes an integrative framing that treats the three AI mechanisms as mutually reinforcing, differentiated from information-centric, analytics-centric, and digital-twin-centric views that examine mechanisms in isolation. For practitioners, the work outlines implementation support mechanisms spanning organization, talent, risk governance, and evaluation. A common failure mode across supply chain AI adoption is the tendency to pursue visible techniques rather than those addressing the chain's weakest mechanism, which the diagnostic use of the four KPI dimensions in Section 5.4 should help identify.

Several limitations constrain the findings. The simulation is synthetic, leaving structural breaks, competitive interactions, and cross-SKU substitution uncaptured. The JD.com case rests on publicly reported data rather than primary interviews, which introduces selection bias toward successful implementations. The framework assumes technical capabilities that small and medium enterprises may lack, and cross-border supply chains face data sovereignty constraints that complicate federated learning across jurisdictions.

Beyond the emerging directions outlined in Section 6.2, a priority for future research is real-data validation through firm-level instrumentation. Partnering with a mid-sized firm willing to instrument a baseline workflow and an AI-enabled workflow for side-by-side comparison would sharpen effect-size estimates and test the framework under operational conditions that synthetic simulation cannot capture. The framework stands as an organizing lens for AI-enabled supply chain collaboration, to be refined as evidence accumulates across industries and regulatory contexts.

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Author contributions

Conceptualization, Y.X. and K.L.O.; methodology, Y.X.; software, Y.X.; validation, Y.X. and K.L.O.; formal analysis, Y.X.; investigation, Y.X.; data curation, Y.X.; writing—original draft preparation, Y.X.; writing—review and editing, K.L.O.; visualization, Y.X.; supervision, K.L.O.; project administration, K.L.O. All authors have read and agreed to the published version of the manuscript.

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Data availability

All data in this study were generated by numerical simulation and can be fully reproduced from the demand model in Equation (1) with the stated parameters and random seed; no external datasets were generated or analysed. The JD.com case analysis draws entirely on publicly available data reported in Hu et al. (2024).

Declarations

Conflict of interest

The authors declare that there is no conflict of interest.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

All authors have given their consent.

Additional information

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