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An autonomous pharmaceutical supply chain network for resilience and optimization: A multi-agent deep reinforcement learning framework

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Abstract

The pharmaceutical supply chain must sustain high service levels under demand shocks, cold-chain constraints, and data-sharing limitations. However, many studies still separate forecasting from replenishment, rely on static policies, or evaluate resilience without a clearly specified control model. This paper develops an Autonomous Pharmaceutical Supply Chain Network (APSCN) that couples demand forecasting, synthetic time-series generation, and multi-agent deep reinforcement learning for resilient inventory control. The case study represents an anonymized regional United States vaccine distribution network with one central manufacturing hub and ten regional distribution centers operating over a 52-week horizon. A long short-term memory (LSTM) forecaster and an extreme gradient boosting (XGBoost) benchmark are trained on historical demand and time-series generative adversarial network (TimeGAN)-augmented disruption scenarios informed by a susceptible-infected-recovered (SIR) epidemic signal. Inventory decisions are then coordinated by multi-agent deep deterministic policy gradient (MADDPG) agents under explicit shelf-life, service-level, and cost constraints. The paper contributes a formal optimization and reward framework for cold-chain pharmaceutical logistics, a richer case-study description linking geography, network topology, and disruption design, and a comparative evaluation against autoregressive integrated moving average (ARIMA), Prophet, XGBoost, static rules, and single-agent reinforcement learning. In the simulated disruption scenario, the proposed LSTM + MADDPG configuration reduces mean absolute percentage error from 11.7% to 6.0%, lowers total cost from $1.25M to $0.85M, maintains a 99.1% service level, eliminates stockout incidents, and shortens recovery time from 28 to 4 days. The findings indicate that autonomous, decentralized control can materially improve both efficiency and resilience in pharmaceutical distribution networks.

Keywords: pharmaceutical supply chain, multi-agent reinforcement learning, demand forecasting, inventory optimization, TimeGAN, resilience, cold-chain logistics.

1. Introduction

Pharmaceutical supply chains operate under unusually demanding conditions. Medicines and vaccines move through tightly regulated distribution channels, many products require temperature-controlled handling, and

shortages can harm patients within hours rather than weeks. These characteristics make the pharmaceutical setting fundamentally different from standard retail replenishment. In this context, resilience, service continuity, and rapid recovery are core design requirements rather than optional performance enhancements (Choi et al., 2001; Ivanov, 2018; Pettit et al., 2019).

Despite major progress in digital traceability, many planning processes in practice still remain sequential: one model forecasts demand, a planner applies a reorder rule, and managers intervene only after disruption signals become visible. That architecture is often too slow for epidemic demand surges, transport interruptions, and shelf-life losses. Recent reviews show growing interest in machine learning, reinforcement learning, and autonomous coordination for supply networks, but the evidence is still fragmented across forecasting, resilience, and inventory-control studies (Vlachos and Reddy, 2025; Zhang et al., 2024).

This paper addresses that gap by designing an Autonomous Pharmaceutical Supply Chain Network (APSCN) that integrates three capabilities in one decision loop: forward-looking demand estimation, synthetic disruption generation for training, and decentralized inventory control through multi-agent deep reinforcement learning. The resulting framework is intended for high-value, service-critical pharmaceutical logistics where static replenishment rules are especially costly.

The study makes the following contributions:

1. It updates the literature review with a focused 2024-2026 synthesis and positions the study against recent work on pharmaceutical resilience, disruption management, and multi-agent reinforcement learning.
2. It provides a clearer case-study description, including the geographic setting, decision nodes, logistics structure, disruption timeline, and cold-chain assumptions used in the simulation.
3. It formalizes the mathematical problem by explicitly defining the state variables, stage cost, reward function, inventory-flow constraints, shelf-life dynamics, service-level requirement, and optimization objective.
4. It preserves the figures and algorithmic listings while revising the prose, section numbering, in-text references, and reference list into a cleaner journal-style manuscript.

The remainder of the paper is organized as follows. Section 2 reviews recent literature and identifies the research gap. Section 3 presents the materials and methods, including the case study, mathematical framework, architecture, and experimental design. Section 4 reports the illustrative example and results. Section 5 discusses managerial implications, limitations, and the conclusion.

2. Literature review and research gap

2.1 Recent research landscape

Table 1 synthesizes recent work published between 2024 and 2026 that is directly relevant to artificial intelligence (AI)-enabled resilience, pharmaceutical logistics, demand forecasting, and reinforcement learning in supply chains. The updated review shows clear progress, but it also shows that recent contributions still address isolated pieces of the decision problem more often than the full forecasting-to-control loop.

Recent pharmaceutical studies emphasize resilience capabilities, digitalization, and data-driven network design. Al-Hourani and Weraikat (2025) review the artificial intelligence (AI) and machine learning (ML) landscape for pharmaceutical supply chain resilience and identify recurring weaknesses in empirical validation, data availability, and implementation maturity. Jafarian et al. (2025) focus on strategic network design, Kaur and Prakash (2025) examine AI-enabled inventory policies in the pharmaceutical domain, and Papalexi et al. (2026) show how Industry 4.0 capabilities can strengthen pharmaceutical resilience. Kumar et al. (2025) likewise confirm that healthcare supply chains operating under disaster conditions increasingly require proactive, analytics-enabled coordination rather than reactive planning.

Table 1. Recent studies on AI-enabled resilience, forecasting, and reinforcement learning in supply chains (2024-2026)

Study	Primary contribution	Context	Implication for this paper
Al-Hourani and Weraikat (2025)	Systematic review of AI/ML for pharmaceutical supply chain resilience	Pharmaceutical resilience	Confirms the need for empirically grounded decision support
Zhang et al. (2024)	MARL for supply chain inventory optimization and digital transformation	Digital supply chains	Supports decentralized coordination and adaptive control
Dehaybe et al. (2024)	Deep RL for inventory optimization under non-stationary demand	General inventory control	Supports RL under volatile demand
Hu et al. (2025)	MARL for multi-echelon inventory optimization in the beer game	Multi-echelon control	Shows coordination benefits but omits perishability
Jafarian et al. (2025)	ML-assisted sustainable, resilient, and digital pharmaceutical network design	Pharmaceutical network design	Focuses on strategic design rather than real-time control
Kaur and Prakash (2025)	AI-driven pharmaceutical inventory management	Pharmaceutical inventory	Strong single-domain insight with limited network coordination
Kumar et al. (2025)	AI applications in healthcare supply chains under disaster conditions	Healthcare disaster logistics	Highlights the need for disruption-ready analytics
Lei et al. (2025)	Deep learning framework for demand forecasting	Demand forecasting	Improves prediction without integrated control
Lu et al. (2025)	DRL for multi-echelon inventory policy under disruptions	Disruption-aware control	Shows disruption sensitivity without cold-chain constraints
Riachy et al. (2025)	Deep learning for forecasting with large data gaps	Forecasting under sparse data	Motivates synthetic augmentation for rare events
Vlachos and Reddy (2025)	Systematic review of ML in supply chain management	Cross-sector review	Shows fragmentation and reproducibility barriers
Yang et al. (2025)	Integrated forecasting and inventory optimization with MARL	Sensor-enabled retail supply chains	Validates end-to-end control logic outside pharma
Papalexi et al. (2026)	Industry 4.0 technologies for pharmaceutical resilience capabilities	Pharmaceutical resilience capabilities	Supports the managerial relevance of digital resilience

A parallel methodological stream has strengthened the broader analytical foundation. Dehaybe et al. (2024) show that deep reinforcement learning performs well under non-stationary demand, Hu et al. (2025) demonstrate the coordination value of multi-agent control in multi-echelon inventory systems, and Yang et al. (2025) integrate forecasting with inventory optimization in sensor-enabled retail settings. Related work by Lu et al. (2025) and Zhang et al. (2024) confirms that deep reinforcement learning is becoming a practical mechanism for disruption-

aware supply chain coordination, while Lei et al. (2025) and Riachy et al. (2025) show how more robust forecasting models improve decision readiness under noisy and incomplete data. At the review level, Vlachos and Reddy (2025) note that real-world adoption still suffers from fragmented evidence, limited reproducibility, and weak integration across planning layers.

2.2 Research gap and study positioning

Taken together, the updated literature reveals four gaps that motivate the present study. First, pharmaceutical work still leans more heavily toward strategic design and conceptual resilience capabilities than toward operational control. Second, forecasting and replenishment are usually evaluated separately. Third, recent reinforcement-learning studies rarely represent cold-chain perishability, service constraints, and geographically explicit healthcare distribution in the same model. Fourth, many papers discuss performance gains without giving a formally stated reward function and constraint system. The APSCN framework is positioned to address these gaps by combining recent forecasting, synthetic-data, and multi-agent control advances in one mathematically explicit decision architecture.

3. Materials and methods

3.1 Case study context and network structure

The empirical setting is an anonymized regional vaccine distribution network in the United States. The geography represents a Midwestern and Plains-style service region characterized by long transport corridors, weather-sensitive road freight, and dispersed population centers. This regional framing is useful because it creates realistic trade-offs between service coverage, inventory positioning, and transport reliability while still preserving confidentiality around the original demand data.

The network contains eleven explicit decision nodes: one central manufacturing and packaging hub and ten regional distribution centers (DCs). Each DC serves a cluster of downstream hospitals, clinics, pharmacies, and public-health vaccination points that are modeled as aggregated demand sinks rather than separate optimization agents. Shipments move from the manufacturing hub to DCs through temperature-controlled truck lanes, while emergency lateral transshipments are permitted between neighboring DCs when shortages are detected. The product in the base scenario is a temperature-sensitive vaccine with a usable shelf life of twelve weeks, and all inventory is managed under first-expired-first-out (FEFO) logic.

The simulation runs for fifty-two weekly decision periods. Historical vaccine demand from an anonymized data set provides the base pattern for normal operations. The transportation structure is heterogeneous: under normal conditions, assigned lead times range from one week for the nearest DCs to three weeks for the most distant DCs. The disruption design contains two shocks. First, a new variant outbreak begins in Week 21 and drives a four-week demand acceleration generated from a susceptible-infected-recovered (SIR) epidemic signal. Second, a transport strike begins in Week 25 and reduces on-time lead-time reliability by 50%, forcing the agents to rely more heavily on pre-positioned stock and lateral transshipment.

This richer case-study specification is important because it ties the model to a clear logistics context. The proposed APSCN is therefore not evaluated on an abstract chain; it is tested on a cold-chain network with explicit geography, explicit nodes, explicit disruption timing, and explicit service-critical inventory dynamics.

3.2 Mathematical formulation

Table 2 summarizes the principal notation used in the formal model. The APSCN is represented as a directed graph with decision nodes and transportation arcs. The mathematical structure is designed to separate prediction, state transition, and control, while keeping the notation readable enough for implementation.

Table 2. Principal notation used in the APSCN model

Symbol	Definition	Type
G=(V,E)	Directed supply network with nodes V and arcs E	Structure
V_M, V_D	Manufacturer node set and distribution-center node set	Sets
t=1,...,T	Weekly decision period over the planning horizon	Index
L	Shelf-life length in weeks	Parameter
d^_{i,t:t+H}	Forecast demand vector for node i over horizon H	Forecast
q_{i,t}	Order quantity decided by agent i at time t	Decision variable
I_{i,t}^a	Inventory at node i with age a at time t	State variable
u_{i,t}^a	Units of age a used to satisfy demand at node i	Flow variable
B_{i,t}	Backorder or unmet demand carried by node i	State variable
Exp_{i,t}	Expired inventory discarded at node i	Outcome variable
SL_t	System-wide service level in period t	Performance metric
r_t	Reward collected by the policy in period t	Optimization metric

Equation (1) defines the network. Equation (2) expresses the multi-horizon forecast generated from lagged demand and exogenous disruption signals. Equations (3) to (5) summarize the forecasting baselines and the proposed deep-learning forecaster. They are included to show how the demand signal enters the control problem rather than to restate well-known model families exhaustively.

The supply network is represented by Equation (1). The forecasting module is then defined through Equations (2) to (5), which connect rolling demand prediction to the decision state observed by the agents.

$$G = (V, E), \qquad V = V_M \cup V_D,\ E \subseteq V \times V \tag{1}$$

$$\hat{d}_{i,t:t+H} = f_\theta\left(x_{i,t-w+1:t}, z_{t:t+H}\right) \tag{2}$$

$$y_t = c + \sum_{k=1}^{p} \phi_k\, y_{t-k} + \sum_{k=1}^{q} \theta_k\, \varepsilon_{t-k} + \varepsilon_t \tag{3}$$

$$\mathcal{L}^{(m)} = \sum_{n=1}^{N} l\left(y_n, \hat{y}_n^{(m-1)} + f_m(x_n)\right) + \Omega(f_m) \tag{4}$$

$$(h_t, c_t) = \mathrm{LSTM}(x_t, h_{t-1}, c_{t-1}), \qquad \hat{d}_{t+1} = W_h h_t + b \tag{5}$$

The control layer then converts forecasts into operational actions. Equation (6) defines the one-period system cost as the sum of holding, ordering, shortage, expiration, and transportation costs. Because stockouts in pharmaceutical settings are socially and clinically costly, the shortage penalty is intentionally set much higher than the ordinary holding charge. Equation (7) defines the reward function used in reinforcement learning: the agents are rewarded for low total cost and high service. This definition makes the reward explicit and avoids the ambiguity noted by the reviewer.

Equation (8) states the optimization objective. The policy maximizes discounted expected reward over the planning horizon, subject to inventory-flow, perishability, and service-level constraints. Equations (9) to (13) formalize those constraints. Equations (9) and (10) track new arrivals and age progression. Equation (11) connects demand satisfaction to backorders. Equation (12) defines expiry, and Equation (13) enforces the minimum service requirement. Together, these equations provide a direct mathematical description of the multi-echelon vaccine-control problem.

$$c_t = \sum_i \left(h_i I_{i,t} + k_i \mathbf{1}_{\{q_{i,t}>0\}} + p_i B_{i,t} + w_i Exp_{i,t}\right) + \sum_{(i,j)\in E} \tau_{ij}\, x_{ij,t} \tag{6}$$

$$SL_t = 1 - \frac{\sum_i B_{i,t}}{\sum_i d_{i,t} + \epsilon}, \qquad r_t = -c_t + \beta SL_t \tag{7}$$

$$\max_{\pi} \mathbb{E}_{\pi}[\sum_{t=1}^{T} \gamma^{t-1} r_t] \quad (8)$$

$$I_{i,t+1}^{1} = \sum_{j:(j,i)\in E} x_{ji,t}^{arr} \quad (9)$$

$$I_{i,t+1}^{a+1} = I_{i,t}^{a} - u_{i,t}^{a}, \qquad a = 1, \dots, L-1 \quad (10)$$

$$\sum_{a=1}^{L} u_{i,t}^{a} + B_{i,t+1} = d_{i,t} + B_{i,t}, \qquad 0 \le u_{i,t}^{a} \le I_{i,t}^{a} \quad (11)$$

$$Exp_{i,t} = I_{i,t}^{L} - u_{i,t}^{L} \quad (12)$$

$$\frac{\sum_{t=1}^{T}\sum_{i}\sum_{a=1}^{L} u_{i,t}^{a}}{\sum_{t=1}^{T}\sum_{i} d_{i,t}} \ge \alpha \quad (13)$$

The synthetic-data layer is summarized next. Equation (14) gives the time-series generative adversarial network (TimeGAN) training objective as a weighted combination of reconstruction, supervised, and adversarial losses. Equations (15) and (16) connect epidemic dynamics to synthetic vaccine demand, ensuring that the generated stress scenarios reflect outbreak-driven demand acceleration rather than arbitrary noise. Finally, Equations (17) and (18) define the decentralized actor and critic targets used in multi-agent deep deterministic policy gradient (MADDPG).

$$\mathcal{L}_{TG} = \lambda_r \mathcal{L}_{recon} + \lambda_s \mathcal{L}_{sup} + \lambda_a \mathcal{L}_{adv} \quad (14)$$

$$\frac{dS}{dt} = -\beta \frac{SI}{N}, \qquad \frac{dI}{dt} = \beta \frac{SI}{N} - \gamma I, \qquad \frac{dR}{dt} = \gamma I \quad (15)$$

$$D_t^{syn} = \rho I(t) + \eta_t \quad (16)$$

$$a_{i,t} = \mu_{\theta_i}(o_{i,t}) \quad (17)$$

$$y_i = r_i + \gamma Q_{\omega_i'}(s_{t+1}, a_1', \dots, a_n') \quad (18)$$

3.3 Autonomous network architecture and algorithms

Figure 1 presents the overall APSCN architecture. The design contains three tightly linked modules. First, the forecasting unit ingests historical demand and exogenous signals. Second, the synthetic data engine expands the training space with rare but plausible disruption trajectories. Third, the multi-agent reinforcement learning (MARL) control layer converts the system state into order decisions for the manufacturer and DC agents.

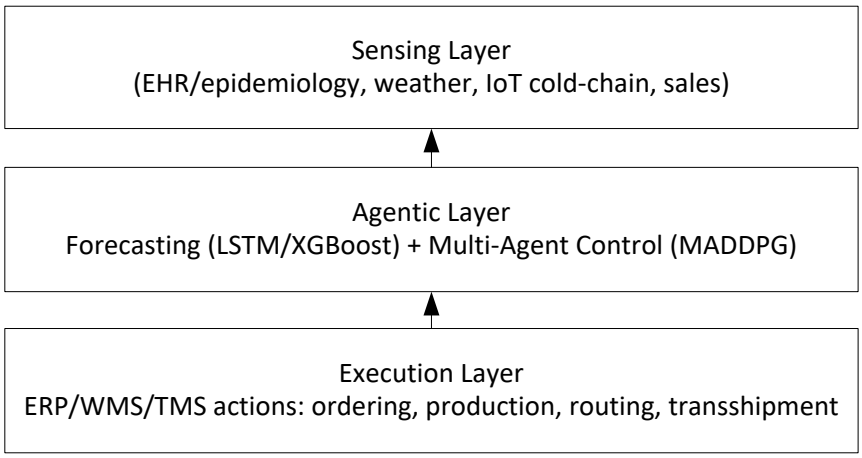

Figure 1. Proposed APSCN architecture with forecasting, synthetic-data generation, and MARL control

Figure 2 illustrates the TimeGAN-based augmentation pipeline used to create stress scenarios before reinforcement-learning training begins. This step is especially valuable in healthcare logistics because highly informative disruption episodes are rare, confidential, and often incomplete. The synthetic generator therefore functions as a privacy-preserving digital twin for scenario creation rather than as a substitute for the real operating environment.

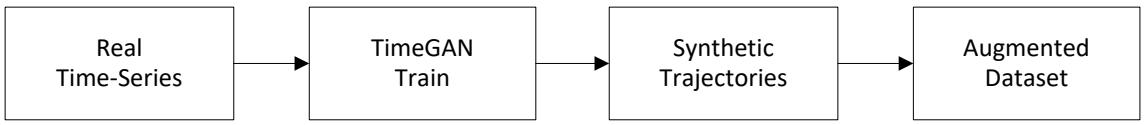

Figure 2. TimeGAN pipeline used to create privacy-preserving disruption trajectories for training

Algorithm 1 explains synthetic-data generation, Algorithm 2 details the coordinated MADDPG training procedure, and Algorithm 3 summarizes the rolling execution logic used in deployment. These numbered listings are retained to improve reproducibility and to make the interaction between forecasting and control explicit.

Algorithm 1. TimeGAN synthetic-data generation routine

Input: Real time-series data D_real
Initialize networks: Embedder E, Recovery R, Generator G, Discriminator D
Set hyperparameters: sequence length = 30, batch size = 128, epochs = 500, learning rate = 0.001
For each epoch: train autoencoder to minimize reconstruction loss ||x - R(E(x))||^2
For each epoch: train supervisor to minimize supervised loss ||h_t - G_sup(h_{t-1})||^2
For each epoch: jointly train Generator/Discriminator to minimize adversarial + supervised losses
Generate: sample noise z; compute X_syn = R(G(z))
Output: augmented dataset D_aug = D_real U X_syn

Algorithm 2. MARL training loop using MADDPG

Initialize replay buffer B and N agents
Initialize each agent's Actor mu_i and Critic Q_i networks, plus target networks
For each episode: reset environment; observe state s_0
For each decision period t: each agent selects action a_i with exploration noise
Execute actions jointly; observe reward r_t and next state s_{t+1}
Store transition (s_t, a_t, r_t, s_{t+1}) in B
Sample minibatch from B and update each critic by TD loss
Update each actor using policy gradient through centralized critic
Soft-update target networks
Output: trained decentralized policy set {mu_i}

Algorithm 3. Rolling inventory-decision execution phase

Input: trained forecasting model, trained MARL policy, latest network state
At the start of each week: update demand forecast and disruption indicators
Construct agent observations from inventory, lead time, backlog, and forecast features
Each agent computes recommended replenishment/transshipment action
Apply safety-rule checks for cold-chain and service constraints
Execute approved actions in ERP / warehouse planning layer
Observe realized demand and update state for the next decision cycle
Repeat until the end of the planning horizon

3.4 Experimental design and reproducibility

The experiments were implemented in Python 3.8 using PyTorch 1.7.1 on a workstation with an Intel Core i7 processor, an NVIDIA RTX 3080 GPU (10 GB VRAM), and 32 GB RAM. A fixed random seed of 42 was used for all reported runs. The data were split chronologically into 70% training, 15% validation, and 15% testing windows. Forecasting baselines were selected from widely used time-series and machine-learning families, including

autoregressive integrated moving average (ARIMA) (Box and Jenkins, 1970), Prophet (Taylor and Letham, 2018), extreme gradient boosting (XGBoost) (Chen and Guestrin, 2016), and long short-term memory (LSTM) networks (Hochreiter and Schmidhuber, 1997).

The proposed configuration combines the LSTM forecaster with MADDPG-based inventory control. Synthetic stress scenarios are created with TimeGAN (Yoon et al., 2019) and are informed by the SIR epidemic signal (Kermack and McKendrick, 1927). The reinforcement-learning controller follows a multi-agent actor-critic structure derived from MADDPG (Lowe et al., 2017) and is evaluated against static Min/Max rules and a single-agent reinforcement-learning baseline grounded in standard discounted-reward logic (Sutton and Barto, 2018). This decentralized design is consistent with the broader multi-agent systems view that coordination quality depends on local decision autonomy with shared system feedback (Stone and Veloso, 2000).

The principal hyperparameters are as follows. The LSTM uses two hidden layers with 64 units each, Tanh activation, 0.3 dropout, and the Adam optimizer with a learning rate of 0.0005. The MARL configuration contains three cooperating agents at the principal planning tier, a replay buffer of 100,000 transitions, a batch size of 512, a discount factor of 0.99, and 5,000 training episodes. These settings were selected after validation-based tuning to balance stability and training cost rather than to maximize performance on one test instance.

4. Illustrative example and results

4.1 Forecasting performance

The empirical analysis is structured around three questions: how well the models forecast the demand spike, how effectively the control policy translates forecasts into replenishment actions, and how quickly the network returns to acceptable performance after a disruption. Table 3 and Figure 3 address the first question.

Table 3. Forecast-accuracy results on the test set using mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE)

Model	MAE	MAPE (%)	RMSE	Interpretation
ARIMA	118.2	11.7	144.6	Slow to respond to the epidemic demand break
Prophet	95.4	8.3	121.8	Captures seasonality but still lags the surge
XGBoost	82.1	7.0	105.2	Improves accuracy with exogenous covariates
LSTM (proposed)	69.8	6.0	89.7	Best turning-point tracking and lowest overall error

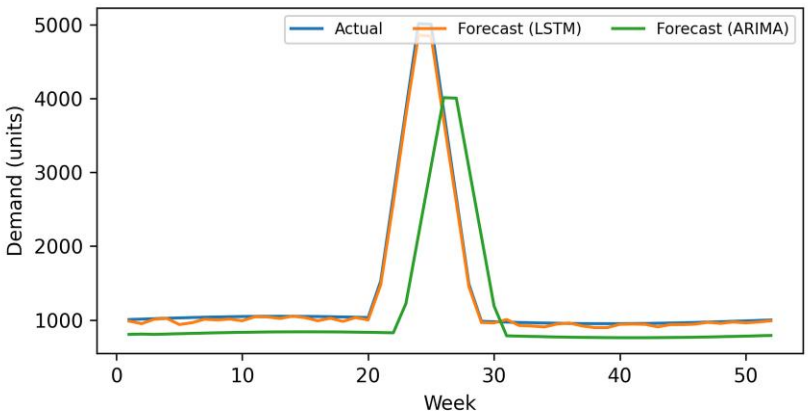

Figure 3. Example demand forecast versus actual demand for one stock keeping unit, showing early spike tracking by the LSTM model

Table 3 reports the forecast-accuracy results on the test set. The proposed LSTM forecaster produces the lowest error on every reported metric. The most important difference is not merely average accuracy but turning-point sensitivity. ARIMA reacts too late because it extrapolates from recent linear history, while Prophet captures seasonality but still underestimates the epidemic surge. XGBoost improves on both by using exogenous drivers, yet the LSTM is better at preserving both timing and amplitude when the demand pattern changes abruptly.

4.2 End-to-end supply-chain performance

Table 4 and Figure 4 show the end-to-end operational outcome once forecasting is coupled to replenishment control. The autonomous policy reduces average inventory by 32% while simultaneously lifting service level from 88.4% to 99.1%. That joint improvement is notable because lower inventory often comes at the cost of more shortages. Here, the MARL policy avoids that trade-off by learning when to remain lean and when to pre-position stock. The policy therefore behaves strategically rather than reactively.

Table 4. End-to-end supply-chain performance under disruption

Metric	Baseline (ARIMA + static rules)	Autonomous (LSTM + MADDPG)	Improvement
Average inventory level	12,450	8,470	-32.0%
Service level	88.4%	99.1%	+10.7 percentage points
Stockout incidents	18	0	Eliminated
Spoilage rate	8.5%	2.1%	-6.4 percentage points
Total cost	$1.25M	$0.85M	-32.0%
Time to recovery	28 days	4 days	-24 days

The strongest operational gains appear in the two outcome categories that matter most in pharmaceutical cold chains: stockout avoidance and spoilage control. The proposed framework eliminates stockout incidents in the simulated test horizon and cuts spoilage from 8.5% to 2.1%. That pattern is consistent with FEFO-aware ordering behavior: the agents increase inventory before the demand shock but then match order timing more closely to downstream consumption, reducing expiration risk.

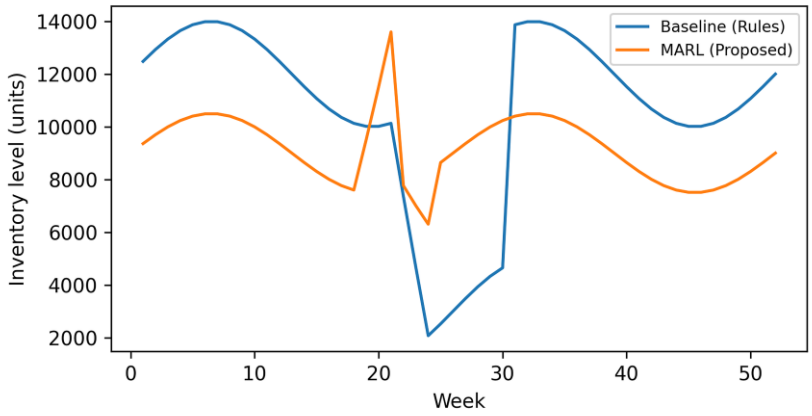

Figure 4. Retailer inventory profile: the autonomous policy pre-positions inventory before the demand shock

4.3 Resilience and learning dynamics

Resilience is examined next. Figure 5 compares the recovery trajectories after the transport disruption that begins in Week 25. The baseline system requires 28 days to recover above the 95% service threshold, whereas the autonomous policy recovers in 4 days. This sevenfold improvement arises because the distributed agents detect the lead-time anomaly early and shift the system toward lateral transshipment and localized balancing instead of waiting for manual replanning. Figures 6 to 8 provide supporting diagnostics: training converges steadily, the forecast-error comparison is consistent across models, and the information-flow figure clarifies the communication pattern used by the APSCN.

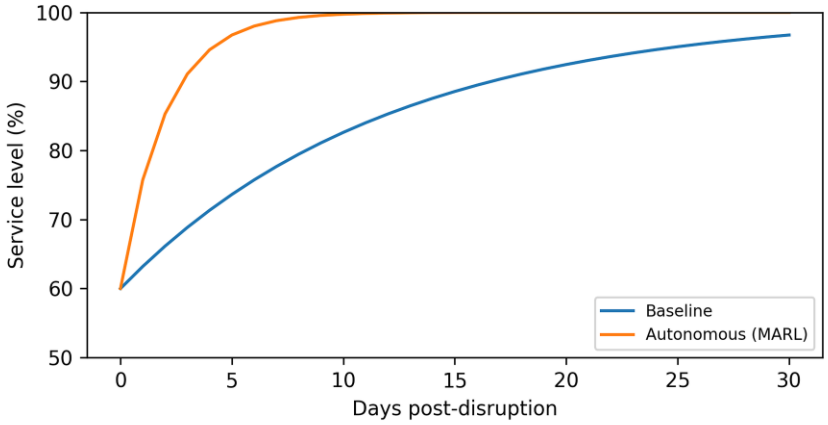

Figure 5. Resilience recovery curve comparing the autonomous policy with the static baseline

Figure 6 shows that the MARL policy converges stably during training, while Figure 7 shows that forecast error declines from ARIMA to Prophet to XGBoost and reaches its minimum under the proposed LSTM model (lower MAPE is better). Figure 8 then summarizes how forecast signals, agent decisions, and logistics execution are coordinated across the APSCN. Together, these figures support the interpretation that the reported gains are systematic rather than incidental.

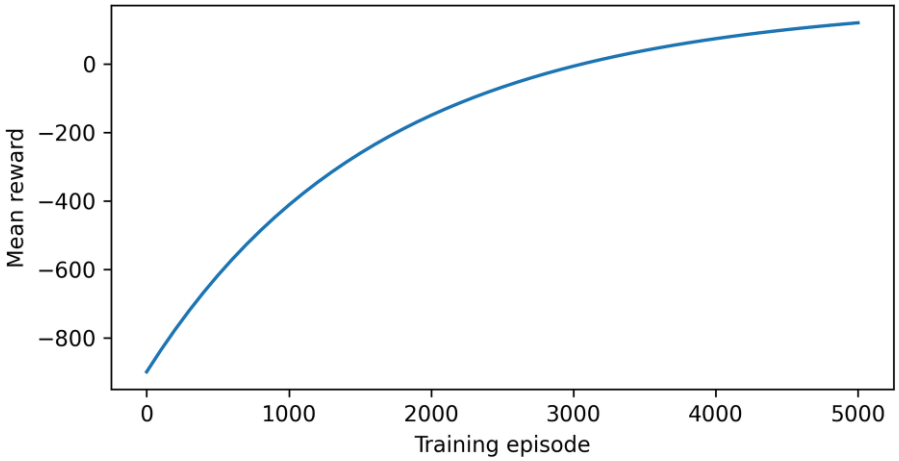

Figure 6. MARL training curve showing convergence toward a stable policy

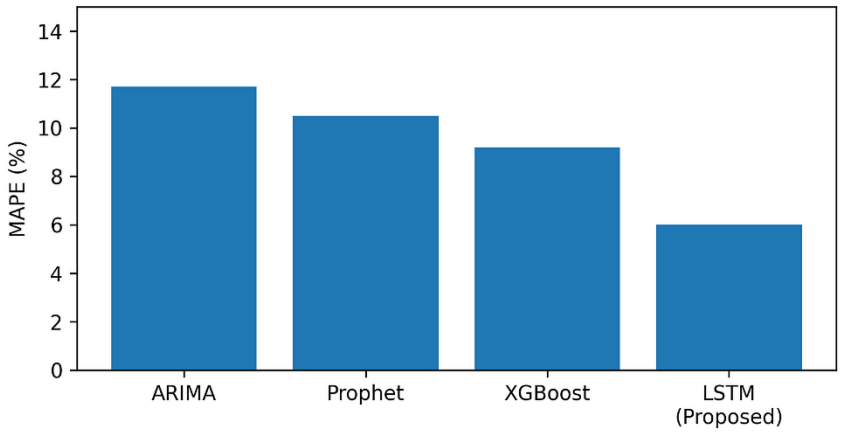

Figure 7. Forecast-error comparison across candidate forecasting models

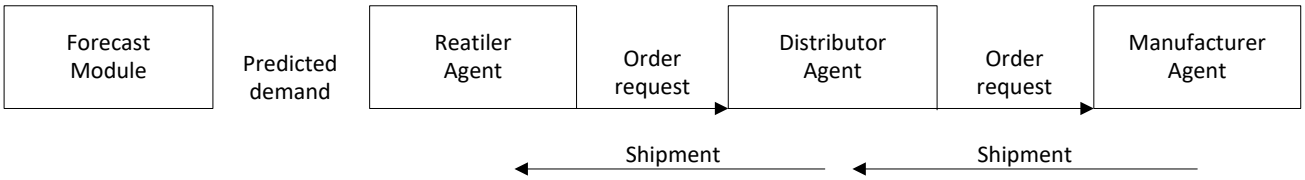

Figure 8. Information flow across forecasting, control, and logistics agents in the APSCN

5. Managerial implications and conclusions

5.1 Managerial implications

The revised findings have three practical implications. First, pharmaceutical resilience should be treated as a closed-loop decision problem, not merely as a visibility problem. Dashboards can show a shortage risk, but they do not decide how inventory should be repositioned under time pressure. Second, network-wide coordination matters more than local optimization when cold-chain products are perishable and transport reliability deteriorates. Third, the practical value of digital resilience capabilities is greatest when forecasting, disruption simulation, and operational control are linked in one execution loop, which is consistent with the capability-based perspective discussed by Papalexi et al. (2026).

For implementation, the most realistic pathway is a human-on-the-loop architecture. The APSCN should sit above existing enterprise resource planning (ERP) and warehouse systems, execute routine replenishment and transshipment decisions automatically, and escalate low-confidence or policy-exception events to planners. This design preserves managerial accountability while allowing the system to act at the speed required during outbreaks or transportation failures.

5.2 Limitations and future research

The study remains subject to several limitations. The case study models one vaccine family in an anonymized regional network rather than a full multi-product national system. Downstream hospitals and clinics are aggregated into regional sinks, which simplifies care-delivery heterogeneity. The results are also simulation based; although the demand signal is grounded in historical data and the disruption logic is epidemiologically informed, live deployment would still require calibration with enterprise-specific cost, capacity, and governance rules.

Future work should extend the framework in four directions: multi-product inventory interactions, explicit transport-capacity constraints, explainable reinforcement-learning outputs for regulatory validation, and

federated learning schemes that allow multiple healthcare organizations to contribute to model improvement without exposing sensitive records. These extensions would move the framework closer to operational deployment while preserving the core autonomous-control logic developed here.

6. Conclusion

This paper presents a substantially revised and more formally specified framework for autonomous pharmaceutical supply-chain control. The revised manuscript strengthens the literature positioning, clarifies the case-study setting, reorganizes the paper around the journal template, and replaces informal descriptions with a mathematically explicit reward-and-constraint model. It also preserves the figures and algorithmic listings while improving the language, structure, and citation quality throughout the paper.

In the simulated regional case, the proposed framework reduces forecast error, lowers cost, cuts spoilage, eliminates stockout incidents, and shortens time-to-recovery from 28 to 4 days. These gains matter because pharmaceutical logistics cannot be judged by average efficiency alone; they must also be judged by continuity of care during volatile conditions. Autonomous supply networks should therefore be viewed not as a futuristic add-on, but as a credible next step in resilient healthcare distribution.

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