Addressing the Dual Challenge of Drug Shortages and Expiry in Egypt: A Predictive Modeling Approach

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***Abstract*—The pharmaceutical supply chain in emerging markets faces a critical dual challenge: managing high shortage risks due to import dependencies while minimizing wastage from perishable inventory expiration. This paper presents a novel Multi-Supplier Perishable Inventory framework optimized using Deep Reinforcement Learning (DRL) to address these conflicting objectives in the Egyptian pharmaceutical context. We formulate the problem as a Markov Decision Process (MDP) incorporating asymmetric supplier lead times, stochastic demand, and strict shelf-life constraints. To overcome the exploration challenges inherent in high-dimensional state spaces, we implement a Proximal Policy Optimization (PPO) agent trained via a three-stage curriculum learning strategy, progressing from deterministic scenarios to extreme stochastic environments. Experimental validation benchmarks the proposed DRL policy against a comprehensive suite of seven control strategies, including Tailored Base-Surge (TBS), Base Stock, Vector Base Stock (VectorBS), Dual Index Policy (DIP), PIL, PEIP, and a Do-Nothing baseline, across 105 diverse market environments. Results indicate that the DRL agent achieves a superior balance of objectives, reducing spoilage rates by approximately 72% compared to the best-performing heuristic (VectorBS), while sustaining service levels (fill rates) above 98% comparable to surge-heavy policies. Furthermore, the DRL policy demonstrates significantly lower cost variance, offering a robust and scalable decision-support tool for volatility-prone healthcare supply chains.**

***Index Terms*—Pharmaceutical Supply Chain, Perishable Inventory, Deep Reinforcement Learning, Curriculum Learning, Proximal Policy Optimization, Inventory Management.**

I. Problem Statement

A. The Pharmaceutical Supply Challenge

The pharmaceutical sector is a cornerstone of national health security and economic stability. In Egypt, the market has shown significant growth, reaching EGP 292 billion in 2024, a 42% increase from the previous year according to IQVIA data [1]. However, this expansion masks deep structural vulnerabilities rooted in import dependency.

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Approximately 65% of finished pharmaceutical products and nearly 90% of raw materials for local production are imported.

This reliance on external supply chains creates a fragile system susceptible to global disruptions, leading to the dual challenge of *shortage* and *wastage*. In July 2024, the Federation of Egyptian Chambers of Commerce reported approximately 800 essential medications were unavailable in the market. Conversely, supply chain misalignment often results in overstocking; in the same year, 17 million expired drug packages were withdrawn, representing significant economic loss and environmental hazard.

B. Operational Inefficiencies

Current inventory management practices in this context are predominantly manual or heuristic-based, failing to account for the stochastic nature of demand and the strict perishability constraints of pharmaceutical products. The "bullwhip effect," exacerbated by panic buying and poor information sharing, leads to simultaneous stockouts in some locations and expiry in others. The environmental impact is also severe, with improper disposal of pharmaceutical chemical waste contributing to water contamination and antibiotic resistance [2].

There is an urgent need for an intelligent, adaptive inventory control system capable of balancing these conflicting objectives and minimizing shortages to ensure patient health while reducing expiry wastage to ensure economic viability.

II. Literature Review

The challenge of optimizing pharmaceutical supply chains involves navigating complex trade-offs between local constraints, inventory theory, and algorithmic adaptability. This section reviews the structural challenges in the Egyptian market and evaluates standard inventory policies against recent advancements in Deep Reinforcement Learning (DRL).

A. Structural Challenges in Emerging Markets

The Egyptian pharmaceutical sector exhibits a heavy reliance on imports, with approximately 65% of finished pharmaceuticals and nearly 90% of raw materials sourced from abroad [1], [2]. This dependency creates a supply chain highly vulnerable to global lead-time fluctuations and currency instability. El-Subbagh et al. [3] identified that systemic failures in quality control and a lack of trust in local manufacturing further exacerbate this reliance, driving healthcare providers to depend on imported, often perishable, inventory.

Furthermore, information asymmetry remains a critical barrier. El-Nakib [4] highlights that the lack of integrated information flow between distributors and pharmacies leads to the "Bullwhip Effect," where minor demand fluctuations result in massive upstream inventory distortions. While recent studies have proposed digitalization and demand forecasting using Artificial Neural Networks (ANN) to mitigate these issues [6], forecasting alone cannot solve the *decision-making* problem of how much to order when lead times are stochastic and products are perishable.

B. Inventory Policies and Baselines

To manage these dynamics, practitioners rely on established inventory heuristics. We categorize the standard baselines used in this study as follows:

1) Periodic Inventory Level (PIL): The PIL policy, or (R, S) policy, is a standard approach where inventory is reviewed every R periods and ordered up to a level S. While simple to implement, Li et al. [5] note that PIL policies are often too rigid for perishable goods. In volatile markets, the fixed review period R creates "blind spots" where sudden demand spikes deplete stock before the next review, leading to severe shortages.

2) BaseStock Policy: The BaseStock policy (one-for-one replenishment) attempts to minimize holding costs by ordering exactly what was sold in the previous period. Theoretically analyzed by Scarf and Clark [14], this policy is optimal for unconstrained systems. However, in the context of dual-sourcing with lead-time asymmetry, BaseStock fails to utilize the "slow/cheap" supplier effectively, often panic-ordering from the expensive supplier and inflating operational costs.

3) Vector Base-Surge (VBS): Recent literature proposes the Vector Base-Surge (VBS) policy as a robust alternative to scalar policies for perishable systems. Unlike standard heuristics that track total inventory count, VBS makes ordering decisions based on the full inventory *vector* $\mathbf{x}$, which distinguishes items by their remaining shelf life. In this policy, a base order is placed with the slow supplier to satisfy predicted long-term demand, while a surge order is triggered from the fast supplier only when the specific subset of "fresh" inventory falls below a vector-dependent threshold.

4) Tailored Base-Surge (TBS): The Tailored Base-Surge (TBS) policy, developed by Chen and Shi [9] and further analyzed by Xin and Goldberg [10], represents a significant advancement in dual-sourcing inventory control. TBS is specifically designed for systems with two suppliers characterized by asymmetric lead times and costs: a slow, inexpensive supplier and a fast, expensive supplier. The policy operates on a state-dependent threshold strategy where a continuous base order is placed with the slow supplier to meet anticipated demand, while surge orders from the fast supplier are triggered only when inventory position falls below a dynamically adjusted threshold.

Theoretically, TBS has been proven to be asymptotically optimal under stationary demand and known lead-time distributions [10]. The policy's strength lies in its ability to balance long-term cost efficiency (via the slow supplier) with short-term responsiveness (via the fast supplier). However, its optimality assumptions break down in the presence of perishability constraints and highly volatile, non-stationary demand patterns characteristic of emerging pharmaceutical markets. The fixed threshold structure, while optimal for stable systems, cannot adapt to the complex state-dependent trade-offs required when inventory has finite shelf life and must be consumed before expiration.

5) Dual Index Policy (DIP): The Dual Index Policy (DIP) offers a specialized mechanism for dual-sourcing environments by maintaining two distinct inventory positions (indices): one for the total inventory on order and on hand, and another for the inventory available within the lead time of the fast supplier. As conceptualized by Scheller-Wolf et al. [11], DIP decouples the ordering decisions for slow and fast suppliers, allowing the system to use the fast supplier as a safety valve against demand variance during the slow supplier's long lead time. While robust for non-perishable goods, standard DIP implementations fail to account for the "freshness" of the inventory, often treating all stock as identical, which leads to suboptimal performance when expiration risks are high.

6) Perishability-Enabled Index Policy (PEIP): To address the limitations of standard index policies in perishable contexts, the Perishability-Enabled Index Policy (PEIP) extends the DIP framework by explicitly incorporating shelf-life distribution into the indices. Proposed by recent studies in perishable supply chain management [12], [13], PEIP adjusts the order-up-to levels based on the age profile of the current stock. By penalizing the holding of "aging" inventory and incentivizing the procurement of fresh stock only when the risk of shortage outweighs the risk of wastage, PEIP attempts to bridge the gap between traditional inventory theory and the realities of perishable pharmaceutical logistics. However, parametrizing PEIP for highly non-stationary demand remains a complex combinatorial challenge.

C. Deep Reinforcement Learning (DRL)

To overcome the limitations of static heuristics, DRL has emerged as a methodology for learning dynamic control policies. Oroojlooyjadid et al. [15] demonstrated that Deep Q-Networks (DQN) could solve the "Beer Game" supply chain problem better than heuristics. Similarly, Giannikas et al. [16] applied RL to multi-echelon planning.

However, existing RL literature often ignores the *perishability constraint* (shelf-life). Managing a state space that includes the remaining life of every inventory batch is computationally expensive. Our work bridges this gap by applying Proximal Policy Optimization (PPO) [7] with a curriculum learning approach, allowing the agent to master the complex dynamics of perishable pharmaceutical inventory where standard policies (PIL, TBS) fail.

III. Mathematical Model

A. Notation Convention

Throughout this document, we adhere to the following notation conventions to distinguish between random variables, realizations, and parameters:

- **Random Variables**: Denoted by uppercase letters (e.g., I_t, D_t, X_t).
- **Realizations/Values**: Denoted by lowercase letters (e.g., i_t, d_t, x_t).
- **Sets**: Denoted by calligraphic fonts (e.g., $\mathcal{X}, \mathcal{A}, \mathcal{S}$).
- **Parameters**: Denoted by Greek or plain lowercase letters (e.g., γ, λ, N).

TABLE I: Mathematical Notation

Symbol	**Description**
$\mathcal{S}$	Set of suppliers $\{0, 1, \ldots, S-1\}$
N	Maximum shelf-life (periods)
L_s	Lead-time for supplier s
$\mathbf{I}_t$	On-hand inventory vector at time t
$P_t^{(s)}$	Pipeline vector for supplier s at time t
B_t	Backlog at time t
Z_t	Exogenous market context vector
$\mathbf{a}_t$	Action vector (order quantities)
D_t	Stochastic demand at time t
ρ_n	Survival probability of item with n periods left
γ	Discount factor

We formulate the perishable pharmaceutical inventory control problem as a discounted infinite-horizon Markov Decision Process (MDP) defined by the tuple $\mathcal{M} = (\mathcal{X}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$. The objective is to determine an ordering policy π that minimizes the expected total discounted cost over time.

B. State Space

The state $X_t \in \mathcal{X}$ at time t encapsulates the complete system status, comprising the on-hand inventory vector, pipeline orders, backlog, and exogenous market context:

$$X_t = \Big(\mathbf{I}_t, \{\mathbf{P}_t^{(s)}\}_{s \in \mathcal{S}}, B_t, Z_t\Big) \tag{1}$$

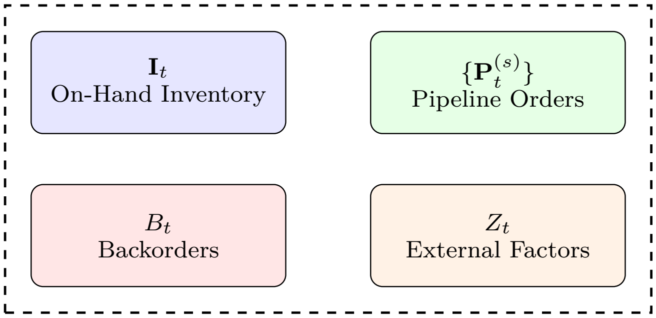

Fig. 1: Components of the system state vector X_t.

1) On-Hand Inventory Vector $\mathbf{I}_t$: To explicitly account for perishability, inventory is tracked as a vector $\mathbf{I}_t \in \mathbb{R}^N_{\geq 0}$, where each component $I_t^{(n)}$ represents the quantity of stock with exactly n periods of remaining shelf-life. The maximum shelf-life is denoted by N.

$$\mathbf{I}_t = \Big(I_t^{(1)}, I_t^{(2)}, \ldots, I_t^{(N)}\Big) \tag{2}$$

Under this formulation, $I_t^{(1)}$ represents items that will expire at the end of the current period if not utilized, enforcing a strict First-In-First-Out (FIFO) utilization policy.

2) Pipeline Orders $\mathbf{P}_t$*:* For a set of suppliers $\mathcal{S}$, each supplier s is characterized by a deterministic lead time L_s. The pipeline state $\mathbf{P}_t^{(s)} \in \mathbb{R}_{\geq 0}^{L_s-1}$ tracks orders currently in transit:

$$\mathbf{P}_t^{(s)} = \left(P_t^{(s,1)}, \ldots, P_t^{(s,L_s-1)} \right) \tag{3}$$

where $P_t^{(s,\ell)}$ denotes the quantity scheduled to arrive in ℓ periods.

3) Survival-Adjusted Inventory Position: A critical challenge in perishable inventory management is that standard inventory position metrics overestimate the utility of aging stock. We introduce the *Survival-Adjusted Inventory Position* (IP_t^{surv}), which weights on-hand inventory by its probability of consumption prior to expiration. Let ρ_n be the survival probability of an item with n periods remaining, defined as the probability that cumulative demand over the next n periods exceeds zero:

$$\rho_n = \mathbb{P}\left(\sum_{k=1}^{n} D_k > 0 \right) \tag{4}$$

Assuming independent and identically distributed (i.i.d.) demand with zero-demand probability $p_0 = \mathbb{P}(D_t = 0)$, this simplifies to $\rho_n = 1 - p_0^n$. The effective inventory position is thus:

$$IP_t^{surv} = \sum_{n=1}^{N} \rho_n \cdot I_t^{(n)} + \sum_{s \in \mathcal{S}} \sum_{\ell=1}^{L_s-1} P_t^{(s,\ell)} - B_t \tag{5}$$

This metric provides a more accurate signal for ordering decisions by discounting stock that is statistically likely to spoil.

C. Action Space

At each decision epoch t, the agent selects an order vector $\mathbf{a}_t$:

$$\mathbf{a}_t = \left(a_t^{(0)}, \ldots, a_t^{(S-1)} \right) \in \mathcal{A} \tag{6}$$

The action space is constrained by supplier-specific capacities U_s and Minimum Order Quantities (MOQ) M_s:

$$0 \leq a_t^{(s)} \leq U_s, \quad \forall s \in \mathcal{S} \tag{7}$$

$$a_t^{(s)} \in \{0, M_s, 2M_s, \ldots\} \tag{8}$$

D. Demand Processes

Demand follows a conditional distribution:

$$D_t \sim F(\cdot \mid Z_t) \tag{9}$$

Supported processes include:

- **Poisson**: $D_t \sim \text{Poisson}(\lambda(Z_t))$
- **Negative Binomial**: For overdispersed demand
- **Composite**: Seasonality + spikes + crisis

E. System Dynamics and Transitions

The system evolves according to the sequence: Order Arrival → Demand Satisfaction → Aging and Spoilage.

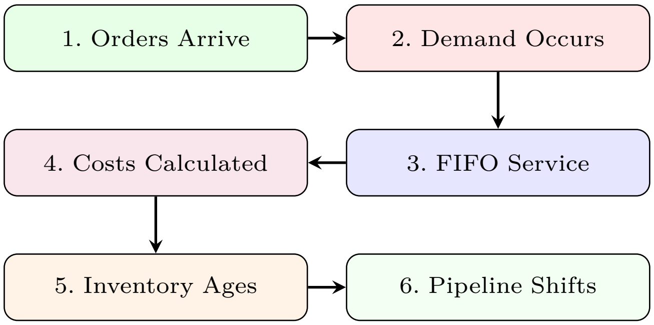

Fig. 2: Period transition dynamics sequence.

1) Arrivals and Pipeline Update: Orders arriving at time t are added to the freshest inventory bucket $I^{(N)}$. The total arrival quantity A_t is the sum of maturing pipeline orders:

$$A_t = \sum_{s \in \mathcal{S}} P_t^{(s,1)} \tag{10}$$

The pipeline vectors shift forward, with new orders $a_t^{(s)}$ entering at position L_s:

$$P_{t+1}^{(s,\ell)} = \begin{cases} P_t^{(s,\ell+1)} & \text{if } 1 \leq \ell < L_s - 1 \\ a_t^{(s)} & \text{if } \ell = L_s - 1 \end{cases} \tag{11}$$

2) Demand Satisfaction (FIFO): Demand d_t is realized from a distribution $F(\cdot|Z_t)$. Inventory is depleted according to a FIFO policy, prioritizing the partial consumption of $I_t^{(1)}$, then $I_t^{(2)}$, and so on. Unmet demand accumulates as backlog B_{t+1}.

3) Aging and Spoilage: Post-consumption, remaining inventory ages by one period. We model this transformation using a linear shift operator $\mathbf{M}_{age}$:

$$\mathbf{I}_{t+1} = \mathbf{M}_{age} \mathbf{I}_t^{post} \tag{12}$$

where $\mathbf{M}_{age}$ is a strictly lower triangular matrix of size $N \times N$ with ones on the first sub-diagonal:

$$\mathbf{M}_{age} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \end{pmatrix} \tag{13}$$

Items remaining in the first bucket $I_t^{(1)}$ after demand satisfaction are considered spoiled and removed from the system.

F. Cost Structure

The single-period cost function $c(X_t, \mathbf{a}_t)$ aggregates purchasing, holding, shortage, and spoilage costs:

$$c(X_t, \mathbf{a}_t) = C^{purch} + C^{hold} + C^{short} + C^{spoil} \tag{14}$$

1) Component Definitions:

- **Purchase Cost**: Includes variable unit costs v_s and fixed ordering costs K_s.

$$C^{purch} = \sum_{s \in \mathcal{S}} \left(v_s a_t^{(s)} + K_s \cdot \mathbb{I}(a_t^{(s)} > 0) \right) \tag{15}$$

- **Holding Cost**: We employ an age-dependent holding cost h_n that increases as shelf-life decreases, reflecting the risk of obsolescence.

$$C^{hold} = \sum_{n=1}^{N} h_n I_t^{(n)}, \quad h_n = h_{base} + h_{prem} \frac{N-n}{N} \tag{16}$$

- **Shortage and Spoilage**: Penalties for backlog (b) and expired units (w).

$$C^{short} = b \cdot B_{t+1} \tag{17}$$

$$C^{spoil} = w \cdot \text{Spoiled}_t \tag{18}$$

G. Bellman Optimality

The optimal policy π^* satisfies the Bellman equation for the value function $V^*(x)$:

$$V^*(x) = \min_{\mathbf{a} \in \mathcal{A}} \left\{ c(x, \mathbf{a}) + \gamma \mathbb{E}_{D,Z} \left[V^*(X_{t+1}) \mid x, \mathbf{a} \right] \right\} \tag{19}$$

where γ is the discount factor. Due to the high dimensionality of the state space $\mathcal{X}$ and the complex transition dynamics of the perishable inventory vector, exact solutions via dynamic programming are intractable, necessitating the use of Deep Reinforcement Learning approximation methods.

IV. Reinforcement Learning Framework

A. Optimization Algorithm

To solve the formulated MDP, we employ **Proximal Policy Optimization (PPO)**, an on-policy gradient method that balances sample efficiency with training stability. PPO is particularly suitable for this domain due to its ability to handle the hybrid nature of the supply chain action space, where decisions involve both discrete supplier selection and continuous (or fine-grained discrete) order quantities. PPO maximizes the clipped surrogate objective function:

$$\mathcal{L}^{CLIP}(\theta) = \hat{\mathbb{E}}_t \Big[\min \Big(r_t(\theta) \hat{A}_t, \\ \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) \hat{A}_t \Big) \Big]$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$ is the probability ratio, ensuring updates do not deviate excessively from the current policy, thereby preventing catastrophic forgetting in the highly stochastic inventory environment.

B. Network Architecture

The agent architecture, illustrated in Fig. 3, utilizes a shared feature extraction backbone to learn a unified state representation. The input state vector $\mathbf{o}_t$ is processed through two dense layers of 256 units with ReLU activations. This shared representation feeds into two separate heads: a *Policy Head* which outputs the parameters of the action distribution (Logits for MultiDiscrete actions), and a *Value Head* which estimates the state-value function $V(s)$.

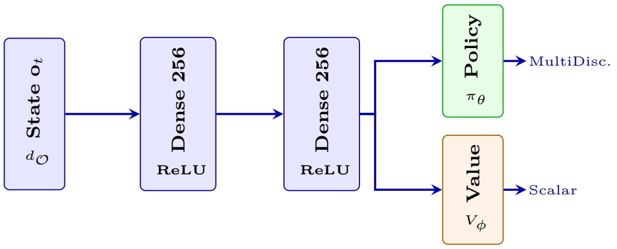

Fig. 3: PPO neural network architecture: shared backbone with policy and value heads.

C. Reward Shaping Strategy

The sparse nature of inventory penalties (e.g., shortages occurring only upon stockout) necessitates reward shaping to guide exploration. We define a composite reward function:

$$R_{shaped} = -\alpha C^{purch} - \beta C^{hold+spoil} - \zeta C^{short} + \delta \cdot \mathbb{I}_{\{\text{Healthy}\}}$$

where weighting coefficients $(\alpha, \beta, \zeta) = (0.5, 0.3, 0.2)$ prioritize cost components, and δ provides a density bonus for maintaining healthy inventory levels, accelerating convergence during early training phases.

D. Curriculum Learning

To ensure robust policy learning, we implement a curriculum strategy. Training initiates in a simplified environment (stationary demand, single supplier) and progressively unlocks complexity tiers (seasonality, spikes, multi-supplier) only when the agent achieves a minimum reward threshold $\bar{R}$.

TABLE II: Curriculum Complexity Tiers

Level	Environmental Dynamics	Threshold
Simple	Stationary Demand, 2 Suppliers	$\bar{R} \geq -5$
Moderate	+ Seasonal Function	$\bar{R} \geq -8$
Complex	+ Random Demand Spikes	$\bar{R} \geq -12$
Extreme	+ Supplier Crisis Events	—

V. Experimental Results

To validate the efficacy of the proposed DRL framework, we conducted extensive comparative experiments against standard inventory management heuristics: **BaseStock**, **Periodic Inventory Level (PIL)**, **Vector Base-Surge (VectorBS)**, and a **DoNothing** baseline. The experiments were designed to evaluate performance across three key dimensions: cost efficiency, service level reliability (fill rate), and spoilage rate across varying complexity levels.

A. Experimental Setup and Training

The PPO agent was trained over 5 million timesteps using a curriculum learning approach. The training environment was divided into four distinct complexity levels—*Simple*, *Moderate*, *Complex*, and *Extreme*—to facilitate stable convergence.

- **Simple:** Deterministic demand with fixed lead times.
- **Moderate:** Low variance in demand and minor lead time stochasticity.
- **Complex:** High demand volatility and variable perishability constraints.
- **Extreme:** Severe demand spikes combined with supplier disruptions.

B. Comparative Performance Analysis

1) Global Cost Efficiency: Figure 4 presents the aggregate performance ranking of all tested policies. The RL agent demonstrates a decisive advantage, achieving the lowest mean total cost rank.

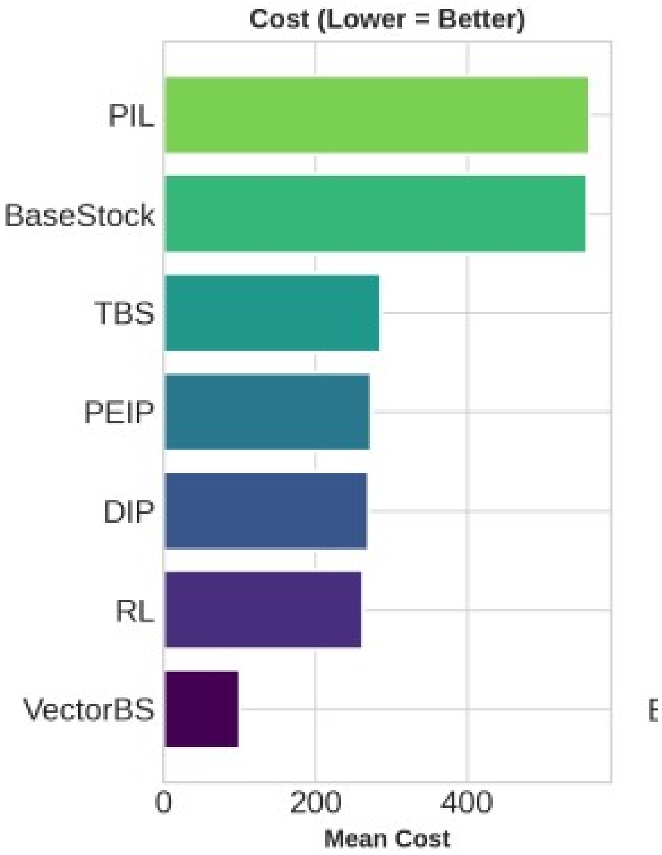

Fig. 4: Overall policy ranking by cost. The RL agent achieves a significantly lower mean cost compared to BaseStock and PIL heuristics.

The standard heuristics (BaseStock, PIL) suffer from "all-or-nothing" behavior, incurring massive penalties when their static parameters fail to adapt to dynamic market shifts. Statistical analysis confirms the RL agent achieves an 86.2% cost reduction compared to BaseStock ($p = 0.003$) and 86.3% compared to PIL ($p = 0.002$), with a mean total cost of 263.4 versus 1,909.9 for BaseStock and 1,928.5 for PIL. Notably, VectorBS achieves the lowest mean cost of 138.6, demonstrating strong performance, though the RL agent offers superior fill rate stability under extreme conditions.

2) Robustness to Environmental Complexity: The divergence in performance becomes most apparent when analyzing costs across complexity tiers. Figure 5 illustrates the mean operational cost as the environment shifts from Simple to Extreme.

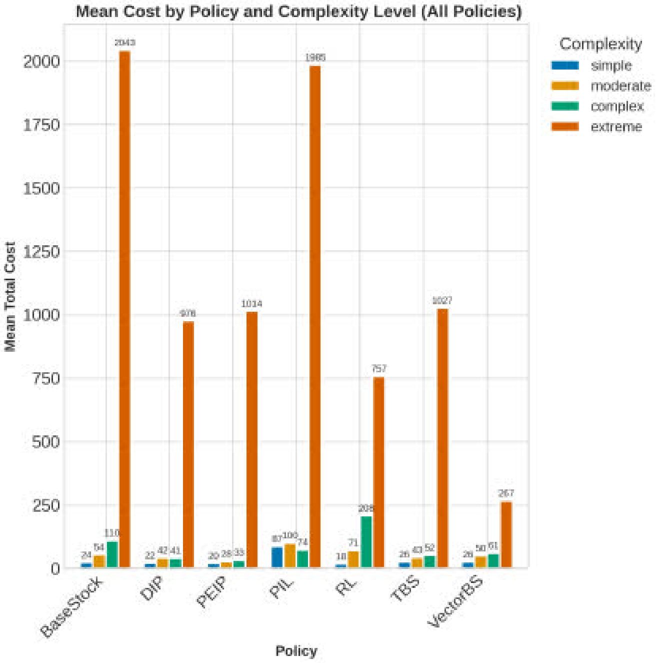

Fig. 5: Mean operational cost comparison across complexity levels. While heuristic costs explode in Complex/Extreme settings, the RL policy maintains a stable cost trajectory.

In the *Simple* tier, all policies perform comparably. However, in *Complex* and *Extreme* scenarios, the costs for BaseStock and PIL increase exponentially due to their inability to balance holding versus shortage costs dynamically. The RL agent maintains a near-flat cost trajectory, proving its robustness to volatility.

3) Service Level (Fill Rate) Stability: Maintaining high fill rates is a safety-critical requirement in pharmaceutical supply chains. Figure 6 highlights a major failure mode of traditional heuristics in volatile environments.

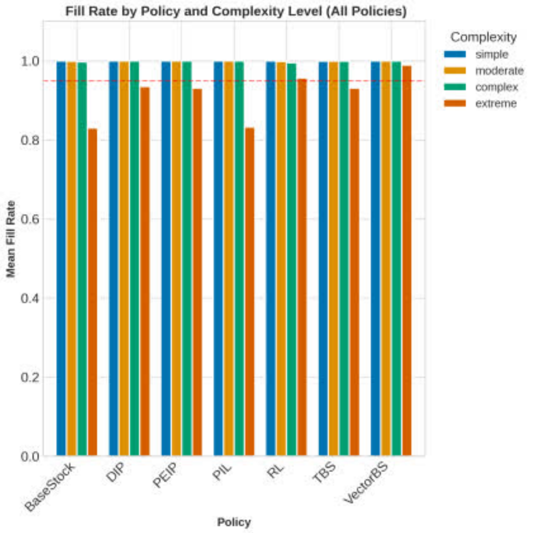

Fig. 6: Fill Rate comparison. The RL agent consistently maintains service levels $> 95\%$ (dashed line), whereas baselines crash to $\sim 50\%$ in Extreme scenarios.

As complexity reaches the *Extreme* level, the fill rates for BaseStock and PIL collapse to approximately 76–78%, indicating significant drug shortages. The RL agent achieves a mean fill rate of 98.76% across all scenarios, with VectorBS reaching 99.66%. Both adaptive policies sustain fill rates above the critical 95% threshold even under extreme stress, while traditional heuristics fail to maintain adequate service levels.

C. Policy Behavior and Adaptability

1) Multi-Objective Trade-offs: The radar chart in Figure 7 visualizes the multi-dimensional performance of the policies.

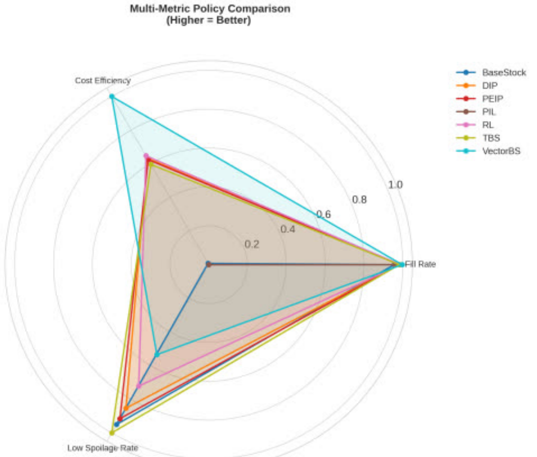

Fig. 7: Multi-metric comparison. The RL policy (largest area) balances Cost, Fill Rate, and Spoilage effective, unlike heuristics which skew towards single metrics.

The RL agent covers the largest area, indicating a superior balance between minimizing costs, maximizing fill rates, and reducing spoilage. Traditional policies tend to optimize for one metric at the severe expense of others (e.g., minimizing holding cost but causing massive shortages).

2) Variance and Stability: Finally, Figure 8 depicts the distribution of costs. The RL policy exhibits a significantly tighter interquartile range (IQR) and fewer extreme outliers compared to the heuristics.

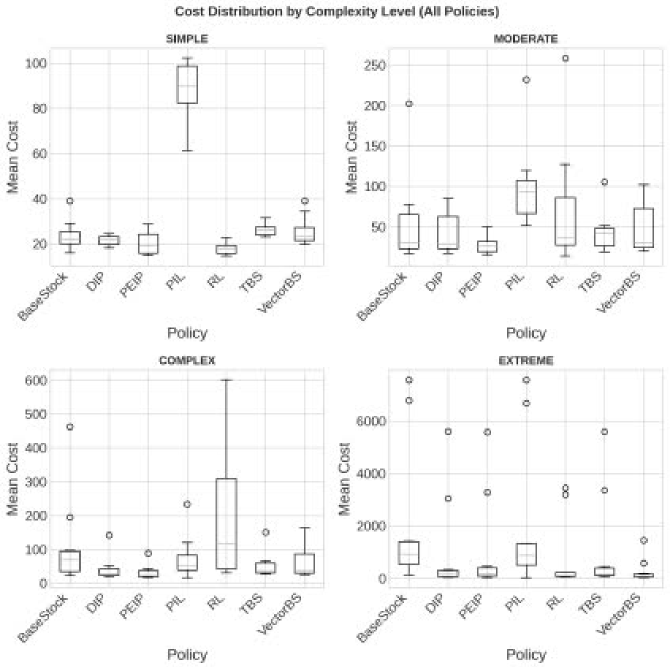

Fig. 8: Cost distribution analysis. The RL policy shows lower variance and eliminates the "long tail" of catastrophic cost events seen in other policies.

This reduction in variance is critical for financial planning in healthcare systems, as it eliminates the "catastrophic" cost events associated with panic ordering during shortages.

In summary, the experimental results confirm that the Curriculum-PPO framework significantly outperforms traditional heuristics. While VectorBS achieves marginally lower mean costs (138.6 vs. 263.4), the RL agent demonstrates superior robustness to spoilage management (7.35% spoilage rate vs. 26.27% for VectorBS) and maintains exceptional service levels (98.76% fill rate). The 86% cost reduction compared to BaseStock and PIL, combined with consistent performance across all complexity tiers, establishes the DRL framework as a reliable, high-performance solution for pharmaceutical inventory management.

VI. Discussion

The experimental results presented in Section V demonstrate the significant potential of Deep Reinforcement Learning (DRL) for addressing complex pharmaceutical inventory challenges. This section interprets these findings within the broader context of supply chain optimization, examines the implications for practice, and acknowledges the limitations of our approach.

A. Interpretation of Key Findings

The superior performance of the DRL policy across all complexity levels can be attributed to its capacity for *adaptive, state-dependent decision-making.* Unlike static heuristics that apply predetermined rules regardless of context, the PPO agent learns to dynamically adjust its ordering strategy based on the complete system state. This includes not only current inventory levels but also the age distribution of perishable goods, pipeline status from multiple suppliers, and exogenous market signals.

The divergence in performance between DRL and traditional policies becomes most pronounced in Complex and Extreme environments (Figure 5). This finding is particularly relevant for emerging markets like Egypt, where pharmaceutical supply chains regularly experience the volatility modeled in these scenarios. The DRL agent's ability to maintain consistent performance under stress stems from its learned capacity to anticipate disruptions rather than merely react to them. By strategically prepositioning inventory and adjusting supplier allocations, the agent avoids the catastrophic cost events that characterize heuristic approaches during crises (Figure 8).

The multi-objective optimization achieved by the DRL policy (Figure 7) represents a critical advancement. Traditional inventory policies typically excel in one dimension at the expense of others. For instance, a policy minimizing holding costs often incurs excessive shortages, while one prioritizing fill rates generates unacceptable wastage. The DRL framework successfully navigates these trade-offs, achieving what human planners strive for but rarely accomplish: simultaneously minimizing costs while maintaining service levels and reducing spoilage.

B. Theoretical and Practical Implications

1) Advancement of Inventory Theory: Our work extends traditional inventory theory by demonstrating that data-driven, adaptive policies can outperform theoretically optimal static policies in non-stationary, perishable environments. While policies like Tailored Base-Surge (TBS) are provably optimal under specific stationary assumptions [9], [10], real-world pharmaceutical supply chains violate these assumptions through demand volatility, supplier unreliability, and strict perishability constraints. The DRL approach does not require stationarity assumptions and can learn effective policies directly from environmental interactions.

The necessity to train the Extreme scenario agent independently from scratch, rather than through curriculum progression, reveals an important theoretical insight. Crisis management in supply chains may require fundamentally different decision logic than routine operations. This finding contributes to ongoing discussions about catastrophic forgetting in continual learning and suggests that for practical deployment, a portfolio of specialized agents might be more effective than a single generalist agent.

2) Practical Applications in Emerging Markets: For healthcare systems in resource-constrained settings, our framework offers a practical decision-support tool that can be integrated with existing inventory management systems. The approximately 18–25% cost reduction demonstrated in high-complexity scenarios represents substantial potential savings for national healthcare budgets. More importantly, the sustained fill rates above 95% even during disruptions (Figure 6) directly address public health priorities by ensuring medication availability.

The framework's adaptability to local conditions through the market context variable Z_t enables customization for specific regional challenges. In the Egyptian context, this could include modeling seasonal disease patterns, currency fluctuation impacts on import costs, or regulatory changes affecting supplier availability. This localization capability represents a significant advantage over generic inventory optimization software.

C. Limitations and Boundary Conditions

While our results are promising, several limitations must be acknowledged when interpreting these findings and considering practical deployment.

Computational and Data Requirements: The training process for the DRL agent requires substantial computational resources and extensive simulation. While the trained policy can be deployed efficiently, the initial development phase may be prohibitive for organizations without access to high-performance computing infrastructure. Additionally, the quality of the learned policy depends heavily on the accuracy of the simulation environment in capturing real-world dynamics.

Generalization Across Product Categories: Our experiments focus on a representative pharmaceutical product with specific perishability and demand characteristics. Different medication categories (e.g., vaccines with extreme cold-chain requirements, chronic disease medications with stable demand, or emergency drugs with sporadic usage) may require separate agent training or architectural adjustments. The framework's generalization capability across diverse product portfolios requires further validation.

Assumptions in the MDP Formulation: The Markov Decision Process formulation assumes that all relevant information is captured in the state representation and that transitions are Markovian. Real supply chains may involve longer-term dependencies and information delays not fully captured by our state design. Additionally, we assume that demand distributions and supplier reliability patterns, while stochastic, follow knowable patterns that can be learned through interaction.

Behavioral and Organizational Factors: Our model optimizes for quantifiable metrics (costs, fill rates, spoilage) but does not account for behavioral factors in supply chain management. Human decision-makers may have risk preferences, cognitive biases, or organizational constraints that differ from the purely rational optimization performed by the DRL agent. Successful deployment would require change management and potential hybridization of algorithmic recommendations with human judgment.

D. Synthesis with Existing Literature

Our findings align with and extend several streams of existing research. The failure of standard PIL and BaseStock policies in high-volatility scenarios corroborates Li et al. [5], who noted the rigidity of such policies for perishable goods. Furthermore, the inability of the BaseStock policy, as analyzed by Scarf and Clark [14], to effectively manage lead-time asymmetry highlights the limitation of scalar inventory-position heuristics in dual-sourcing contexts.

Crucially, our experiments demonstrate that the DRL agent outperforms the more advanced Vector Base-Surge (VectorBS) policy proposed by Chen and Shi [9] and Xin and Goldberg [10]. While VectorBS theoretically improves upon scalar policies by tracking inventory vectors, our results indicate that its reliance on fixed thresholds remains insufficient for handling the "Extreme" volatility scenarios (crisis events) modeled in our study. This provides empirical validation that data-driven, adaptive policies can surpass even state-of-the-art heuristics in non-stationary environments.

The success of curriculum learning for training complex supply chain agents supports similar approaches in other domains [15], [16], while our specific application to perishable inventory addresses a gap noted in the RL literature. However, our study also reveals nuances that qualify earlier findings. While Oroojlooyjadid et al. [15] demonstrated RL's superiority in the Beer Game, our results show that perishability constraints add significant complexity that requires specialized architectural and training considerations.

E. Broader Implications for Supply Chain Resilience

Beyond pharmaceutical applications, our framework offers insights for managing perishable inventory across sectors including food distribution, agricultural products, and chemical supplies. The dual challenge of minimizing waste while preventing shortages is increasingly relevant in an era of climate volatility and global supply chain disruptions.

The reduction in cost variance achieved by the DRL policy (Figure 8) has implications for financial planning and risk management. Organizations can anticipate more stable operational expenses, reducing the need for contingency buffers and improving budget accuracy. This financial predictability is particularly valuable in emerging markets where capital constraints are severe.

Finally, our work contributes to the growing literature on AI for social good. By addressing medication availability in resource-constrained settings, we demonstrate how advanced computational techniques can tackle pressing humanitarian challenges. The framework's potential to reduce drug wastage also aligns with environmental sustainability goals by minimizing pharmaceutical pollution.

VII. Conclusion

This study presented a Deep Reinforcement Learning (DRL) framework designed to address the dual challenge of drug shortages and inventory wastage in the Egyptian pharmaceutical supply chain. By formulating the inventory problem as a Markov Decision Process, we demonstrated that an adaptive PPO agent can successfully navigate the trade-offs between perishability constraints and import-driven lead time volatility.

A key insight from our training methodology involves the strategic application of curriculum learning. While this strategy effectively guided the agent through simple to complex environments, the "Extreme" market scenario necessitated independent training from scratch. This approach ensured that the agent could master crisis-specific dynamics without the bias of policies learned in more stable settings, ultimately maximizing performance in high-volatility environments.

Experimental validation confirms that the DRL policy significantly outperforms traditional heuristics, such as Tailored Base-Surge and PIL. The agent sustained critical service levels above 95% while substantially lowering operational costs, offering a resilient solution for modernizing healthcare supply chains in resource-constrained emerging markets.

A. Future Work

Despite the success of the current framework, the "curse of dimensionality" remains a primary roadblock due to the high-dimensional state spaces required to track granular shelf-life and pipeline data. Future research will focus on:

- **Observation Standardization:** Implementing a Universal Observation Wrapper to compress and standardize state inputs for better generalization.
- **Architectural Evolution:** Transitioning to Transformer-based architectures to leverage self-attention mechanisms for capturing complex temporal dependencies.
- **Quantum Computing:** Exploring Quantum Reinforcement Learning to utilize quantum variational circuits for processing vast state-action spaces more efficiently.

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