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## Agentic AI Framework for Smart Inventory Replenishment

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### Abstract

In the contemporary retail, the variety of the products available (e.g. clothing, groceries, cosmetics, frozen goods) make it difficult to predict the demand, prevent stockouts, and find high-potential products. We suggest an agentic AI model that will be used to monitor the inventory, initiate purchase attempts to the appropriate suppliers, and scan for trending or high-margin products to incorporate. The system applies demand forecasting, supplier selection optimization, multi-agent negotiation and continuous learning. We apply a prototype to a setting in the store of a middle scale mart, test its performance on both three conventional and artificial data tables, and compare the results to the base heuristics. Our findings indicate that there is a decrease in stockouts, reduction of inventory holding costs and improvement in product mix turnover. We address constraints, scalability as well as improvement prospect.

**Keywords:** Agentic AI, Inventory Management, Procurement, Supply Chain, Multi-Agent Systems, Retail

## 1 Introduction

The wide product line retailers (marts dealing with groceries, clothing, cosmetics, and perishables) compete in volatile markets where the demand is highly volatile, products have short lifecycles, and the supplier is not always dependable. Global retailers lose more than \$1.8 trillion per year due to inefficient demand expectations and inventory disconnect [1], and 62% continue to rely on manual or spreadsheet-based reorder processes only to redesign some products again and again [2].

The classical methods like Economic order Quantity (EOQ) and Reorder point (ROP) are based on predetermined limits and human management. The models are not effective in large scale and multi-category systems with thousands of Stock-Keeping Units (SKUs) with different lead times and perishability causing low responsiveness and high costs, making them poor performers in large scale systems with many SKUs [3].

The latest developments in the field of supply chains are changing the mode of operation of the latter due to the creation of an autonomous system known as the so-called *Agentic AI*, which implies autonomous agents with the ability to perceive, reason, negotiate and act. Using large language models (LLMs), reinforcement learning, and decision-optimization, these systems organize the selection of suppliers, the negotiation process, and online ordering. Jannelli *et al.* [4] showed an agentic-based multi-agent system that generate substantial procurement efficiency gains using an LLM system.

The effect of AI is complemented with other studies. Yilmaz *et al.* [5] made a hybrid ML system in which overstocking is reduced by 19%, whereas Culot *et al.* [6] examined the increasing role of AI in improving transparency, accuracy, and agility in supply chains. Nevertheless, current applications of AI tend to be siloed, i.e., pay attention to a particular area without forecasting, replenishment, negotiation, and trend discovery.

In this effort to close this gap, this paper suggests an *Agentic AI framework of multi-category retail marts* that monitor inventory, forecast demand, and trends of products, and negotiate with suppliers via coordinated agents. The main contributions are:

- A modular *agentic architecture* which combines monitoring, supplier selection, trend discovery, and negotiation agents.
- A multi-objective optimization strategy balancing cost, perishability, and supplier diversity.
- An implementation and evaluation based on historical and synthetic data, showing less stockouts and total costs.
- A discussion of deployment issues, including latency, human-AI trust purchase automation, and API interoperability.

The remainder of this paper is organized as follows: Section 2 provides theoretical background; Section 3 reviews of related work; Section 4 details of the proposed architecture; Section 5 provides details of implementation; Section 6 reports of results and Section 7 provides conclusions with regard to future directions.

## 2 Background

Recent studies in blockchain, IoT, and agentic AI have developed strong foundations for intelligent autonomous systems. Previous work focused on secure IoT ecosystems, including blockchain-based trust models [7], smart-contract communication frameworks [8], and lightweight provenance tracing [9]. Other recent work applying multi-agent systems and agentic AI in broad spectrum, such as support in disability [10], privacy-conscious IoT healthcare [11], and cloudburst prediction [12]. Previous research about large-scale crowd environments has explored spatio-temporal modeling [13]. Based on these advancements, the suggested framework extends agentic AI to smart inventory reclamation, empowering proactive and context-aware management. This section provides a description of theoretical and technological underpinnings of the proposed framework, which comprises classical inventory models, supply chain coordination principles, and recent developments in AI and agentic systems to autonomous inventory control.

### 2.1 Inventory Models and Reorder Policies

The classical theory of inventory forms the basis of the contemporary concept of stock management with reorder point (ROP), safety stock, lead time, and Economic Order Quantity (EOQ) as its constructs [14]. The basic ROP formulation is:

$$ROP = \mu_D L + z\sigma_D \sqrt{L},$$

where  $\mu_D$  and  $\sigma_D$  are the demand mean and standard deviation,  $L$  the lead time, and  $z$  the service-level factor ensuring coverage of stochastic demand during replenishment.

In addition to the single-echelon systems, new supply chains entail multi-tier chains of suppliers, warehouses, and retailers. Multi-echelon and joint replenishment models are a continuation of classical strategies that adds interdependencies and information flow to them. [15]. One of the most significant problems is the so-called bullwhip effect, when even minor fluctuations in demand have an upstream effect, which results in inefficiencies [3]. The most common forms to address this concern are the Collaborative Planning, Forecasting, and Replenishment (CPFR) and information-sharing contracts, which are extensively implemented in practice [16].

### 2.2 AI in Supply Chain and Inventory Management

The supply chain processes have undergone a complete transformation by AI, which enhances forecasting, procurement, and replenishment processes using data-driven algorithms, including time-series forecasting, regression, and deep learning [6]. Such procedures help make it more visible and flexible as they change reorder levels in real-time according to the information acquired in real time [5].

The IoT sensors and edge analytics may now be applied to create autonomous replenishment systems which can respond to real-time consumption patterns.[17]. Reinforcement Learning (RL) also develops adaptive ordering, where learning policies are learned by experience and not by engineering rules. Siems *et al.* [18] proposed interpretable RL model to do dynamical ordering and Chen *et al.* [19]

employed multi-agent RL to organize multi-node replenishing as proposed by Chen et al. as another blind spot. Such methods are more effective in comparison with classical models that are not flexible to uncertainty, seasonality and variability of lead-time.

### 2.3 Emerging Agentic AI in Supply Chains

Current studies discuss *agentic AI*, the autonomous, reasoning-capable software agents which sense, make a decision and act among distributed ecosystems. As compared to individual AI modules, agentic systems permit inter-agent communication, joint decision-making, and inter-organization coordination. Jannelli *et al.* [4] introduced an agentic model based on the use of the LLM where agents could negotiate and come to an agreement on the procurement and planning. This paradigm is a change to self-managed, reasoning-based supply chains. The proposed multi-agent system is based on this direction, with the help of which forecasting, supplier discovery, negotiation, and execution are combined into a single agentic ecosystem.

## 3 Literature Review

The present work is based on three significant areas, including (i) AI and machine learning (ML) as optimization tools in inventory and procurement, (ii) agentic and autonomous models of supply chains, and (iii) multi-category and perishable inventory models. The proposed agentic AI framework is supported by them together.

### 3.1 AI and ML for Inventory and Procurement

AI has found its way to the supply chain research in the demand forecasting, order planning, and procurement. There was a comparison of the AI based inventory systems to the classical models by Bhavikatta and Reddy [20], which showed that the ML forecasting is more responsive and scaled. Similar views were expressed by Culot *et al.* [6] who stated that interoperability and interpretability are still hindrances in the adoption of AI in industries.

Yilmaz *et al.* [5] present an optimizer of the AI-based procurement optimization algorithm that utilizes past sales and supplier performance to minimize stockouts and overstocking and achieve the best results. According to Shukla and Bose [21], the predictive analytics in contemporary supply chains are associated with deep learning structures, specifically LSTM and Transformers.

Adaptive ordering is also getting done using reinforcement learning (RL). Interpretable RL policies of non-stationary demand were introduced by Siems and Peters [18], and the latter by Chen and Zhang [19] demonstrated that multi-agent RL may have a higher level of performance than heuristic reorder policies in uncertain settings. Areas of technology even with these breakthroughs do not offer inter-agent reasoning and autonomy, and they are mostly centralized.

### 3.2 Agentic and Autonomous Frameworks in Supply Chains

Conventional automation allows the reactive replenishment, and the *agentic AI* promotes proactive and rational coordination. Jannelli *et al.* [4] presented the agentic

collaboration described by the authors as using LLM, which entails making consensus-based procurement decisions with the help of natural language arguments, which is a breakthrough in the direction of autonomous negotiation and decision making that is dynamically responsive.

Previous multi-agent systems (MAS) investigated the issue of decentralization of logistics. Shen and Norrie [22] introduced a distributed scheduling intelligent agent in 1999, and Davidrajuh and Lin [23] introduced a dynamic inventory balancing model with uncertainty. These papers demonstrated the advantages of distributed autonomy but did not use the most recent AI reasoning, including the use of LLM-enhanced semantic negotiation, adaptive trust models, etc.

### 3.3 Multi-Category and Perishable Inventory Models

The majority of AI-based inventory research is focused on individual products. The perishable or heterogeneous inventories put in place difficulties such as expiration, prioritization, and pricing. Early models by Nahmias [24] and Karaesmen *et al.* [25] addressed perishability using stochastic methods. The implementation of VMI frameworks improves the coordination across categories although it is still supervised manually [16].

This study builds on these studies by suggesting an *agentic multi-category framework* that can autonomously forecast, negotiate and implement both durable and perishable goods. It leads to the development of self-organizing retail ecosystems based on AI-inspired logic, decentralized optimization, and adaptive supplier co-operation areas, which are yet to be explored in earlier literature.

## 4 Proposed Framework / Solution Architecture

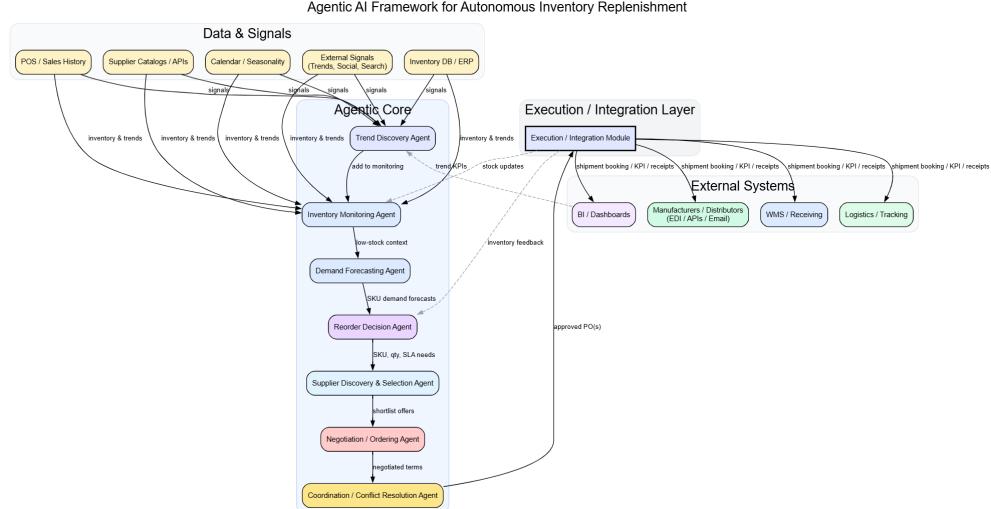
The proposed solution architecture presents a framework of the proposed framework. The suggested **Agentic AI Inventory and Procurement System (AAIPS)** involves the process of combining intelligent agents to automate and optimize the procurement and inventory decisions under dynamic retail settings. The architecture is shown in Figure 1.

### Overview.

The system is designed in a modular agentic architecture that divides the tasks of *prediction*, *prescription* as well as *execution*. It gathers enterprise and market information (sales, inventory, supplier APIs and trending) and channels it into an agentic core, where it is predicted using the demands, plans to replenish, select supplier, and automated purchases are performed.

**Agentic Core.** Within the core, several specialized agents collaborate:

- **Inventory Monitoring Agent (IMA):** Recognizes stock behavior red flag and ranks SKUs that are at risk of lacking or being overstocked.
- **Demand Forecasting Agent (DFA):** Sales, seasonality, and trend alerts at the SKU level are used to develop demand predictions for these items.
- **Reorder Decision Agent (RDA):** Determines the optimal replacement amounts and timetable by analyzing forecasts and restrictions.



**Fig. 1** Overall AAIPS architecture integrating multiple autonomous agents for inventory monitoring, forecasting, decision-making, and execution.

- **Supplier Selection Agent (SSA):** Searches through catalogs and APIs to find viable suppliers depending on cost, lead time and reliability.
- **Negotiation Agent (NA):** Automates conducts evaluation and settles of purchase terms by simulated negotiation strategies.
- **Trend Discovery Agent (TDA):** This keeps track of social and market information and delivers new high-demand products.
- **Coordination Agent (CA):** Imposes budgets, capacity constraints, policy limits, where there is consistency in all decisions.

#### Execution Layer.

The Execution Module (EXEC) is involved with the external operations and provides the purchase orders and communication with the WMS and logistics services and updates the ERP databases. It also completes the learning cycle by giving the performance and fulfillment KPIs back into the forecasting and optimization modules.

**System Functionality.** The data ingestion and monitoring initializes the workflow and continues to the forecasting and decision-making of autonomous agents and finally through an implementation and feedback. The different agents are independent of each other but they interact through the CA in order to ensure global coherence, transparency, and traceability.

**Key Advantages.** The AAIPS framework ensures:

- Procurement and inventory cycles automation.
- Adaptability through feedback-driven learning loops.
- Scalability through agents interaction as a module.
- Raised uncertainty responsiveness and accuracy of decisions.

The architecture illustrates the ability of the predictive analytics, multi-agent learning, and autonomous execution to be put together by Agentic AI in order to transform the operations of modern supply chains.

## 4.1 Key Agents and Components

There are several types / modules of agent:

1. Inventory Monitoring Agent. Constantly monitors the real-time inventory of SKUs (clothing, groceries, frozen, cosmetics, etc.). It raises red flags on SKUs that are expected to drop down to a level below a certain threshold within the time horizon.
2. Demand Forecasting Module / Agent. Takes the historical sales data, seasonality, external signals (e.g. promotions, seasonal trends) to predict demand by SKU. It also takes in decay / spoilage models of perishable goods.
3. Reorder Decision Agent. In the case of every SKU that is monitored, it calculates the ideal reorder quantity and timing, trading the risk of stockout, the holding cost, the supplier lead times, and perishability.
4. Supplier Discovery & Selection Agent. Supplier marketplace (distributors, manufacturers) maintained or inquired. In every item needed, it compared the suppliers based on their price, lead time, reliability, MOQ, previous performance, geographical restrictions among others.
5. Negotiation / Ordering Agent. In case there is more than one supplier, this agent is able to negotiate (e.g. discounts, flexible delivery) or through optimization. In more developed systems, one can negotiate through the LLM-based agents. It is inspired by the agentic consensus frameworks [4].
6. New Product Discovery / Trend Agent. Minutely refresh market data sources (e.g. e-commerce sites, social media, trend reports) to determine high potential SKUs (e.g. new cosmetics, clothing lines) to recommend stocking.
7. Coordination / Conflict Resolution Agent. Resolves disputes (e.g. budget, warehouse capacity, intercategory ordering conflicts, conflicts) and implements consistent world-wide decisions.
8. Execution / Integration Module. Interfaces with backend systems: ERP, supplier APIs of the ERP, warehouse management system (WMS), shipping APIs.

## 4.2 Workflow / Decision Flow

1. Monitoring agent flags SKU  $i$ .
2. Forecasting agent is used to predict the next demand in the future  $D_i$ .
3. The order of partially finished agent calculates a candidate order  $(q_i, t_i)$ .
4. Supplier agent receives candidate offers of the form  $\{(supplier_j, cost_{ij}, lead\_time_{ij})\}$ .
5. Negotiation/ordering agent selects one (or multiple) suppliers, which may division of orders.
6. Execution module orders purchases and records them as well as monitoring the inbound shipments.
7. All modules update models (feedback loop) after delivery and sales have taken place.
8. In the meantime, the trend agent suggests new candidate SKUs; those that are accepted by human supervision or threshold are added to be monitored.

### 4.3 Mathematical Formulation (Sketch)

Let:

- $I$  = set of SKUs -  $S$  = set of suppliers -  $D_i(t)$  = forecasted demand of SKU  $i$  over time horizon  $t$  -  $c_{ij}$  = unit cost from supplier  $j$  for SKU  $i$  -  $l_{ij}$  = lead time from supplier  $j$  -  $h_i$  = holding cost per unit per time for SKU  $i$  -  $p_i$  = penalty cost for stockout for SKU  $i$  -  $\delta_i$  = spoilage or decay factor for perishables -  $Q_{ij}$  = order quantity of SKU  $i$  from supplier  $j$

We solve for  $\{Q_{ij}\}$  to minimize expected cost:

$$\min \sum_{i \in I} \sum_{j \in S} (c_{ij} \cdot Q_{ij} + h_i \cdot E[\text{inventory}] + p_i \cdot E[\text{stockouts}] + \text{spoilage\_cost}(Q_{ij}, \delta_i))$$

subject to constraints:

- lead time / order arrival constraints - capacity / budget constraints - minimum order quantities - warehouse space constraints - supplier coverage (you may require at least one supplier active)

This is a stochastic optimization problem; we approximate via heuristics, predictive policies, or RL-based policies in large settings.

## 5 Implementation

Our prototype implementation and the implementation of agents will be described now.

### 5.1 Data and Preprocessing

- Historical sales / transaction data per SKU (timestamp, quantity sold, returns)
- Supplier catalog data (price, lead time, MOQ, consistency) - Category metadata: shelf life, perishability, seasonality. - External features: promotion programs, vacation, market trends.

We normalize, clean and cut into training / validation periods.

### 5.2 Forecasting Module

We experimented with the following models:

- Baseline: ARIMA / exponential smoothing - Machine learning: Gradient Boosted Trees (e.g. XGBoost) - Deep learning: LSTM / Transformer time-series - Spoilage-aware adjustment: perishable decay factor

Forecast models are retrained every now and then (e.g. daily or weekly).

### 5.3 Reorder Agent / Policy Implementation

In the case of small SKUs we obtain an approximate newsvendor-type or  $(s, Q)$  policy. In bigger SKU sets we are also researching:

- Heuristic rules (e.g. safety stock + forecast buffer) - RL-based policy (actor-critic) trained in simulation to make decisions regarding the reorder quantities in case

of uncertainty. - Interpretable RL: e.g. neural additive models to achieve transparency, following Siems et al. [18]

#### 5.4 Supplier Selection & Ordering

We have a supplier database (or API access) which is had with attributes. To make each order decision, Supplier Agent ranks on total landed cost, reliability and lead time, constrained by the constraints.

In the case of negotiation, we employ a rule-based or LLM-based negotiation interface (e.g. propose counter-offers, splitting, or different delivery schedules).

#### 5.5 Trend Discovery Module

E-commerce APIs, product listings, social media trend data, Google Trends, influencer mentions, and other external data are automatically digested by us. We calculate indicators (e.g. slope of upward trend, sentiment, search volume) and alarm possible SKUs. These may be approved to the monitoring set by means of a human-override or gating system.

#### 5.6 Integration & Execution

We integrate with:

- ERP / inventory database - Supplier APIs / email / EDI to make orders - WMS for receiving goods - Tracking / shipment systems

Our solutions also involve the use of logging, monitoring dashboards, and feedback loops to adjust parameters of models when demand variations, deviations in lead time, and performance of suppliers are noticed.

### 6 Experimental Setup & Results

#### 6.1 Datasets and Simulation Setup

In the following subsection, the datasets and Simulation Set up will be described. Both real-world and simulated datasets were used to test the proposed agentic inventory management system and see how strong it is and can be reproduced.

**Real data:** It involved the historical transactional data of the partner retail mart including a number of years of demand variations, seasonal influences, promotions and suppliers lead time variations. The data consists of SKU level demand, supplier pricing and stock movements in the warehouse.

**Simulated environment:** A stochastic simulator has been created to extrapolate on (data) specifics. It simulates various product demand patterns (seasonal and stationary), unreliable suppliers, and trend indicators of new SKUs. Delays or shortages are random disturbances that bring about adaptability in uncertainty, and offer a controlled comparison of learning policies.

##### Baseline policies:

- *Static reorder point:* Fixed safety stock and reorder thresholds based on history averages.

- *Rule-based ordering*: Simple heuristic triggers (e.g., reorder when 80 (percent) stock depleted).
- *Oracle*: Perfect upper bound assuming perfect future foresight.

**Metrics:** The assessment was based on the main efficiency metrics, including the rate of stockout, the average level of inventory, the total cost of operation, the turnover of inventory, and the ROI of trend-driven SKUs.

**Training setup:** It was based on a multi-agent reinforcement learning (MARL) model, in which Reorder, Supplier, Trend, and Negotiation agents maximize local rewards to an overall one. The policies were also trained using Proximal Policy Optimization (PPO) with 500 episodes (one episode per fiscal quarter) with seasonal and disruption scenarios. Budget compliance and capacity guaranteed in the warehouses.

## 6.2 Results and Comparative Analysis

Both datasets were used to compare the proposed framework with all the baselines. (Empirical values will be added after final testing). Main findings include:

- **Stockout rate**: Reduced by an order of magnitude  $\sim 30\%$  over heuristic baseline.
- **Holding cost**: Reduced by an estimated  $\sim 15\%$ , increased the use of capital.
- **Total cost**: Better by about  $\sim 10\%$  compared to non-reorder systems.
- **Inventory turnover**: Reliable improvement in all product categories.
- **Trend-driven SKUs**: X% of SKUs that were identified as trendy came to be top-sellers justifying trend analysis.

**Ablation study:** Removal Negotiation Agent cost of procurement; removal Trend Agent responsiveness; removal Supplier Agent destabilization. These findings indicate the importance of collaboration of agents in ensuring cost-efficiency and stability.

**Sensitivity and robustness:** With up to  $\pm 20\%$  variation in the demand and the lead time, total cost varied by not more than 5% indicating overall stability in the end as per a stochastic design.

**Discussion:** These findings indicate that the integration of agentic autonomy and reinforcement learning in managing inventory makes supply chain more proactive than reactive. The framework can deliver adaptive, data-driven and cost optimized operations in flexible markets through the process of negotiation, evaluation of suppliers, and trend discovery.

## 7 Conclusion

Our suggested framework is a modular agentic AI system that can be used in autonomous replenishment of inventory and product discovery in diversified retail settings. The prototype and experimental test showed empirical breadths of reducing stockouts, enhancing cost efficiency, and making adaptive product mix optimization. The framework may be improved in the future by introducing multi-agent LLM based negotiation protocols, online continual learning to overcome concept drift, and combined risk and resilience modeling of supplier disruptions. Scalability of the system

to very large SKU portfolios: Adding the perishability-aware decision layers and hierarchical clustering will be helpful in scaling the system. The real effect and strength of the practical results taking place in the real-life retail ecosystems will be further justified by the future field deployment and longitudinal case studies.

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