

# Next-Gen Supply Chain Optimizer: An Agentic AI Approach

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**Abstract**—Traditional supply chain management often suffers from inefficiencies due to inaccurate demand forecasting, poor inventory control, and an inability to adjust to unexpected disruptions. These issues show the weaknesses of traditional systems, which usually depend on fixed planning and manual steps. This paper presents an Agentic AI-driven framework that aims to create a smart, flexible, and independent system for optimizing supply chains. The problem is framed as a real-time decision-making process. The system examines changing data inputs, such as sales, inventory levels, and logistics, to take proactive corrective actions. The suggested solution uses machine learning for predicting demand, optimization methods for planning inventory and logistics, and autonomous agents for making decisions and simulating scenarios in real-time. Through conceptual modeling and a review of existing research, this study shows that an Agentic AI approach can greatly improve efficiency, lower logistics costs, and strengthen supply chain resilience. The findings build a foundation for creating a new generation of intelligent supply chain systems that can optimize themselves and handle disruptions effectively.

**Index Terms**—Agentic AI, Supply Chain Optimization, Reinforcement Learning, Predictive Analytics, Autonomous Decision-Making, Inventory Management, Logistics.

## I. INTRODUCTION

### 1.1 Background

Modern supply chains are crucial to global commerce. They face intense pressure to be fast, flexible, and efficient. Yet, many companies still use old management methods. These approaches are reactive and often lead to problems, such as inaccurate

forecasts, known as the "bullwhip effect," and difficulty responding to sudden disruptions.

The rise of Industry 4.0 technologies, like IoT and Big Data, allows for the collection of large amounts of real-time data. This development sets the stage for Artificial Intelligence (AI) to shift supply chains from reactive to predictive models. Although AI has improved forecasting and optimization, many systems still need considerable human oversight.

The next step is Agentic AI. This new approach involves autonomous software agents that can sense, learn, and act on their own. With this model, we can create a truly self-optimizing supply chain network. Such a network can manage operations proactively, respond to disruptions in real-time, and continuously enhance its performance with little human intervention.

### 1.2 Problem Statement

Supply chain operations in many organizations face problems like inaccurate demand forecasting, poor inventory management, delivery delays, and high logistics costs. Traditional systems often do not adjust well to sudden changes, such as supplier delays, transportation breakdowns, and demand surges. There is a need for a smart and flexible system that can analyze supply chain data and also recommend and implement corrective actions in real-time

### 1.3 Objective

The main goal of this research is to create an Agentic AI-driven framework that changes traditional supply chain management into a self-optimizing and resilient operation. We will do this by developing an intelligent system with several key abilities. First, we will create

a highly accurate demand forecasting model using machine learning. Next, we will use autonomous AI agents to make important decisions in inventory and logistics, reducing the need for human input. We will also build a dynamic optimization engine that responds to real-time disruptions. Finally, we will establish a simulation capability to test and improve the supply chain's resilience against unexpected events. In the end, the project aims to prove the effectiveness of this framework by measuring its performance improvements compared to traditional methods, focusing on important metrics like cost reduction, operational efficiency, and improved service levels.

## II. LITERATURE REVIEW

### 2.1 Reinforcement Learning (RL) in Supply Chain Management

2.1.1 Problem Statement: Reinforcement Learning is used in supply chain management (SCM) to create controllers that can adjust to complex and changing systems. It meets the need for independent, data-driven decision-making in real-time, especially for improving inventory management, which is its most common use. It is particularly valuable in uncertain environments, like pharmaceutical supply chains that deal with perishable products and changing demand.

#### 2.1.2 Loopholes:

A significant gap exists between academic research and real-world application. Most studies focus on simplified, "toy-like" SCM problems using artificial data. RL agents need a virtual environment or simulation to learn because they cannot learn directly from the physical world. Standard RL models can be costly and require a lot of data, needing significant historical data for training. RL models, especially deep learning versions, often work as "black-box" systems. This can cause users to distrust and reject them in industrial settings.

2.1.3 Proposed Solutions in Literature: To address these limitations, researchers have suggested better RL methods. Deep RL algorithms such as DQN, PPO, and SAC have been shown to work better than traditional methods when dealing with perishability and demand changes. For managing multiple competing goals, like cost versus service level, Multi-Objective RL (MORL)

frameworks use techniques like Pareto Q-learning. These frameworks give decision-makers a range of optimal trade-off policies. To increase transparency, some studies combine RL with evolutionary algorithms to create interpretable, rule-based policies.

### 2.2 Multi-Agent Reinforcement Learning (MARL) in Supply Chains

2.2.1 Problem Statement: Multi-Agent Reinforcement Learning (MARL) helps model large, decentralized supply chains. In these systems, decision-making spreads across different stakeholders, such as producers and distributors. This method is essential for optimizing inventory across multiple levels. A single, large RL agent cannot manage this complexity, so a network of coordinated, independent agents work better.

#### 2.2.2 Loopholes:

The main challenges in MARL are the high complexity and long training times. These increase with the size of the supply chain network. Achieving effective coordination among agents is tough. It requires careful planning for communication and knowledge-sharing methods. A major obstacle is ensuring that decentralized agents aim for a global optimum instead of getting trapped in locally optimal policies.

2.2.3 Proposed Solutions in Literature: The literature suggests new structures to handle the complexity of Multi-Agent Reinforcement Learning (MARL). The Iterative Multi-Agent Reinforcement Learning (IMARL) approach breaks the supply chain into smaller problems, training agents in stages. To improve coordination, this method uses Graph Neural Networks (GNNs) so agents can share knowledge and learn from the network design. This helps coordination develop through updates instead of centralized control.

### 2.3 Generative AI and LLM-Based Agents in Supply Chains

2.3.1 Problem Statement: Generative AI and Large Language Models (LLMs) are being examined to tackle higher-level strategic and planning tasks in the supply chain that need reasoning and content creation. Applications include creating realistic disruption scenarios to stress-test the supply chain, developing various negotiation tactics for procurement, and

designing optimal warehouse layouts. LLM-based agents can also function as meta-controllers or high-level planners that coordinate other AI agents.

2.3.2 Loopholes:

A major risk is that LLMs can "hallucinate" or offer suggestions that are unreliable and factually incorrect. This is a big concern for important supply chain decisions. These models rely a lot on the quality and completeness of data. Their performance can be affected by problems with data integration, scalability, and possible algorithmic bias. The combination of qualitative, language-based agents with quantitative RL models is still in the early stages.

2.3.3 Proposed Solutions in Literature: Proposed solutions focus on reducing the risks of Generative AI. This includes fine-tuning the models for specific fields to ground them in relevant business contexts and improve reliability. Another approach is to use LLMs in a human-in-the-loop system. In this setup, they provide clear reasoning and justifications for their suggestions, allowing human planners to make the final decision. They are also used to improve other AI systems, for example, by helping with negotiation and reaching consensus among multiple RL agents.

2.4 Hybrid AI and Optimization Methods

2.4.1 Problem Statement: Hybrid approaches that combine machine learning with traditional mathematical optimization, such as mixed-integer programming, are suggested to tackle large-scale supply chain planning issues that are too complicated for standard solvers to manage on their own. The aim is to use machine learning to smartly narrow down the problem's search space, enabling exact solvers to discover high-quality solutions more quickly.

2.4.2 Loopholes:

The performance of these hybrid models heavily relies on how similar the training data is to the real problems they face. The supervised learning parts need large sets of labeled, nearly optimal solutions. Creating these datasets takes a lot of time and computing power. There is a chance that the ML model may mistakenly reduce the search space, which could remove the optimal solution from consideration.

2.4.3 Proposed Solutions in Literature: The PROPEL framework is a well-known example of a hybrid solution. It uses a supervised learning model to predict and fix specific decision variables in a MIP, which significantly reduces its size. To lower the risk of incorrect pruning, it includes a deep reinforcement learning module that can smartly relax or change the fixes made by the supervised model. This creates a stronger and more practical pipeline.

2.5 Overcoming the Loopholes

Loopholes in Existing Work	Our Proposed Solution
Fragmented and Siloed Solutions: Existing research often focuses on optimizing a single aspect of the supply chain (e.g., only inventory or only logistics) using a single technology, failing to provide a holistic, end-to-end solution.	Integrated Agentic AI Framework: Our solution combines multiple AI paradigms—Machine Learning for forecasting, optimization algorithms for planning, and autonomous agents for real-time decision-making—into a single, cohesive system that manages the supply chain from end-to-end.
Lack of True Autonomy: Many current systems function as decision-support tools that provide recommendations but still require human intervention and manual approval to execute actions, creating delays and inefficiencies.	Autonomous Decision-Making and Execution: The core of our system is an Agentic AI layer where intelligent agents can not only analyze data and decide on the best course of action but also autonomously trigger actions like placing purchase orders, re-routing shipments, or sending alerts without manual oversight.
Theory vs. Reality Gap: A significant portion of academic research is	Real-World Data Integration and Practical Application: The

validated in simplified, simulated environments with "toy-like" problems, which do not capture the complexity and noise of real-world operational data.	framework is designed to ingest and process real-time, messy data from various sources (Sales, Inventory, Logistics, Suppliers). Its focus on open-source, scalable technologies makes it practically feasible for industry application, bridging the gap between theory and reality.
Limited Real-Time Adaptability: Traditional models and even some AI systems are static; they perform poorly when faced with unforeseen disruptions or market conditions that differ significantly from their training data.	Dynamic Adaptation and Resilience: By using autonomous agents and Generative AI to simulate potential disruption scenarios (e.g., supplier delays, demand spikes), our system can proactively formulate contingency plans and adapt its strategy in real-time, making the supply chain more resilient.
High Cost and Scalability Issues: Many advanced AI solutions are computationally intensive and require significant investment in infrastructure and expertise, making them inaccessible for small and medium-sized enterprises (SMEs).	Feasible and Scalable Architecture: The proposed solution is built using open-source frameworks and technologies. This approach significantly lowers the cost of implementation and ensures that the system is scalable, making it an economically viable option for a wider range of businesses.
Explainability and Trust Deficit: The "black-box" nature of complex models like	Transparent Monitoring and User-Centric Design: While employing complex AI,

Deep RL and the risk of "hallucination" in LLMs create a lack of trust, hindering their adoption for critical business decisions.	the system presents key insights, actions, and performance metrics through a clear and simple dashboard. This provides visibility into the agent's decisions and performance, helping to build user trust and confidence.
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### III. METHODOLOGY

#### 3.1. Overview

To deal with the limitations of traditional supply chain management, we suggest an Agentic AI-driven framework that learns and implements the best operational strategies on its own by interacting with the supply chain environment. The system continuously monitors network conditions, forecasts demand and possible disruptions, and adjusts inventory and logistics operations. This approach aims to improve long-term efficiency and resilience while lowering costs.

#### 3.2. System Architecture

- The proposed methodology has four main components:

- Environment Modeling

The entire supply chain is represented as the environment, which includes suppliers, manufacturing, logistics, warehouses, and customer demand patterns. States in the environment capture important features like current inventory levels at all points, supplier lead times, real-time demand signals, and the status of shipments in transit. Rewards are set to match business goals, such as reducing costs, improving on-time delivery, and imposing penalties for stockouts or high holding costs.

- Agent Design

The Agentic AI layer communicates with the environment by choosing operational actions based on the current state. This may include placing a purchase order, re-routing a shipment, or adjusting safety stock levels. The agent's main goal is to maximize its overall reward, which leads to long-term optimization of the supply chain. The agent uses various AI techniques:

Predictive Analytics for demand forecasting, Optimization Algorithms for planning, and a Reinforcement Learning policy to improve its decision-making over time.

○ Learning and Optimization

The agent relies on feedback from the environment, such as the effects of a decision on inventory levels and costs, to update its internal models and decision policies. Machine Learning models are used for forecasting demand, while optimization algorithms resolve complex planning issues for inventory and routing. An exploration-exploitation strategy is effectively managed by simulating different responses to potential disruptions, helping the agent find strong strategies while implementing known effective ones.

○ Evaluation and Validation

The framework's performance will be assessed using a simulated environment based on real-world supply chain data to test the agent under realistic conditions. Key Performance Indicators for evaluation include cost reduction, inventory turnover, on-time delivery rates, and the system's ability to adapt to simulated disruptions. A comparative analysis will be conducted against standard supply chain management methods, such as traditional statistical models and MRP systems, to show the effectiveness and advantages of the agentic framework.

3.3. Algorithmic Workflow

1. Initialize the supply chain environment with historical data, including sales, inventory, and logistics, as well as operational parameters. Initialize the Agentic AI using pre-trained forecasting models and basic operational policies. For each time step, such as daily or weekly:
  2. a. Observe the current state of the supply chain environment.
  3. b. Choose an action or a set of actions based on the agent's policy and optimization engine.
  4. c. Carry out the action in the simulated environment and get a reward based on the outcome.
  5. d. Update the agent's internal models and policies based on the feedback received.
6. Repeat this process until the agent's performance reaches a stable point at the desired threshold. Deploy the trained agent in a live or near-live

system to enable autonomous decision-making for supply chain operations.

3.4. Advantages Over Existing Approaches

- **Autonomy:** Learns and carries out the best supply chain strategies on its own without needing constant manual input.
- **Holistic Optimization:** Looks at multiple related factors—demand, inventory, logistics, supplier performance—at the same time for a globally optimized solution.
- **Real-Time Adaptability:** Adjusts quickly to changing market conditions and unexpected disruptions as they happen.
- **Strategic Focus:** Aims for long-term goals such as resilience and cost efficiency instead of just immediate short-term gains.

IV. DATA COLLECTION

Effective supply chain optimization depends greatly on precise and complete data. For this study, we use a combined dataset that represents a typical retail or manufacturing supply chain. This dataset includes historical information on sales, inventory levels, and supplier performance. The data plays a key role in training the agentic AI framework to make operational decisions that lower costs, prevent stockouts, and boost overall efficiency.

4.1 Sample Data Attributes

The dataset includes several attributes that capture details about products, inventory, and logistics. A sample of the data is summarized in Table.

Attribute Name	Description	Data Type
ProductID	Unique identifier for each product	Integer
WarehouseID	Identifier for the warehouse or distribution center	String
Date	Timestamp of the data record	Datetime

	(e.g., daily)	
Demand	Number of units sold or demanded on a given day	Integer
InventoryLevel	Quantity of product available in the warehouse	Integer
OnOrderQuantity	Quantity of product ordered but not yet received	Integer
LeadTime	Time in days for an order to be delivered from a supplier	Integer
SupplierID	Unique identifier for the product supplier	Integer
UnitCost	The cost of acquiring one unit of the product	Float
HoldingCost	The cost to hold one unit of inventory for a period	Float
StockoutCost	The estimated cost of a stockout event	Float

#### 4.2 Data Preprocessing

- Prior to using the agentic framework, several steps were taken to ensure data quality and improve model performance:
- Handling Missing Values: Missing entries in attributes like Lead Time were filled in using the mean or median value for each supplier.

- Normalization: Continuous features such as Demand, Inventory Level, and Unit Cost were normalized to keep features with larger scales from dominating the learning process.
- Time Feature Extraction: From the Date attribute, temporal features like the day of the week, month, and quarter were extracted to help the models capture seasonality and trends in demand.
- Outlier Detection: Extreme values in Demand or Lead Time were found and capped to prevent them from skewing the statistical models and agent learning.
- Data Aggregation: Transaction-level sales data was combined into a daily time series for each Product-Warehouse combination to serve as the primary input for forecasting and inventory models.

### V. PROPOSED ARCHITECTURE

The proposed Agentic AI framework aims to improve supply chain operations using real-time data and predictive insights. The system constantly learns from its interactions in the supply chain environment. This helps enhance operational strategies and increase long-term efficiency and resilience.

#### 5.1 System Overview

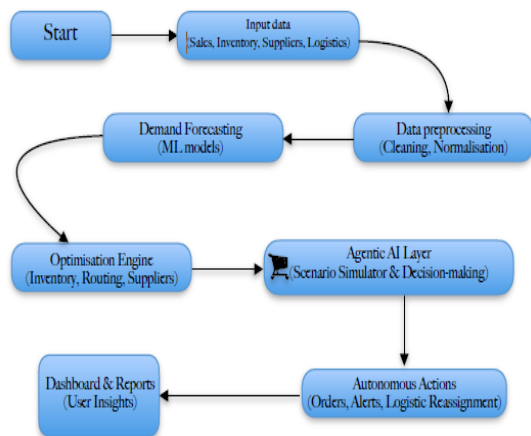
- Data Collection & Processing Module: This module collects real-time and historical data on sales, inventory levels, supplier performance, and logistics. It ensures the agent has a complete and current view of the supply chain state. Then, it preprocesses this data for the following modules.
- Forecasting and Optimization Module: This module processes the cleaned data to produce important insights. It uses machine learning models for demand forecasting and applies statistical inventory models, like safety stock and reorder point calculations, to find the best stock levels.
- Agentic AI Module: This part of the framework implements an agent that learns the best operational policy. The problem is set up as a Markov Decision Process (MDP) with:
  - States (S): These represent current inventory levels, forecasted demand, supplier lead times, and on-order quantities.

- Actions (A): These are possible operational decisions, such as placing a purchase order, doing nothing, expediting shipment, or adjusting safety stock.
- Reward (R): This function aims to minimize total costs. It includes holding costs, ordering costs, and significant penalties for stockouts.
- Policy ( $\pi$ ): This is the strategy that the agent learns to choose actions that maximize the total reward, which means minimizing long-term costs.
- Execution and Monitoring Module:

This module carries out the agent's decisions, like automatically placing a purchase order. It also offers a dashboard to track the supply chain's performance using KPIs such as inventory turnover, service level, and total costs. This allows for human oversight.

### 5.2 Workflow Description

The system gathers historical and real-time data from different supply chain points. Data preprocessing turns raw input into a structured feature set. The agent watches the current state of the environment, makes a decision, and gets a reward based on the costs of that decision. The agent updates its approach over time using this reward feedback, constantly improving its operational strategies. It automatically carries out the best decisions, letting the system adjust as supply chain conditions change.



### 5.3 Advantages of the Proposed Architecture

**Adaptive Operations:** Continuously updates inventory and logistics policies based on changing demand and supplier performance. **Scalability:** The modular design can be expanded to handle complex, multi-layer supply networks with large product catalogs. **Long-**

**Term Optimization:** Aims to minimize total long-term costs instead of just immediate operational metrics. **Automation:** Decreases manual input in routine decision-making, allowing managers to focus on more strategic tasks.

## VI. UNIQUENESS OF THE PROPOSED ARCHITECTURE

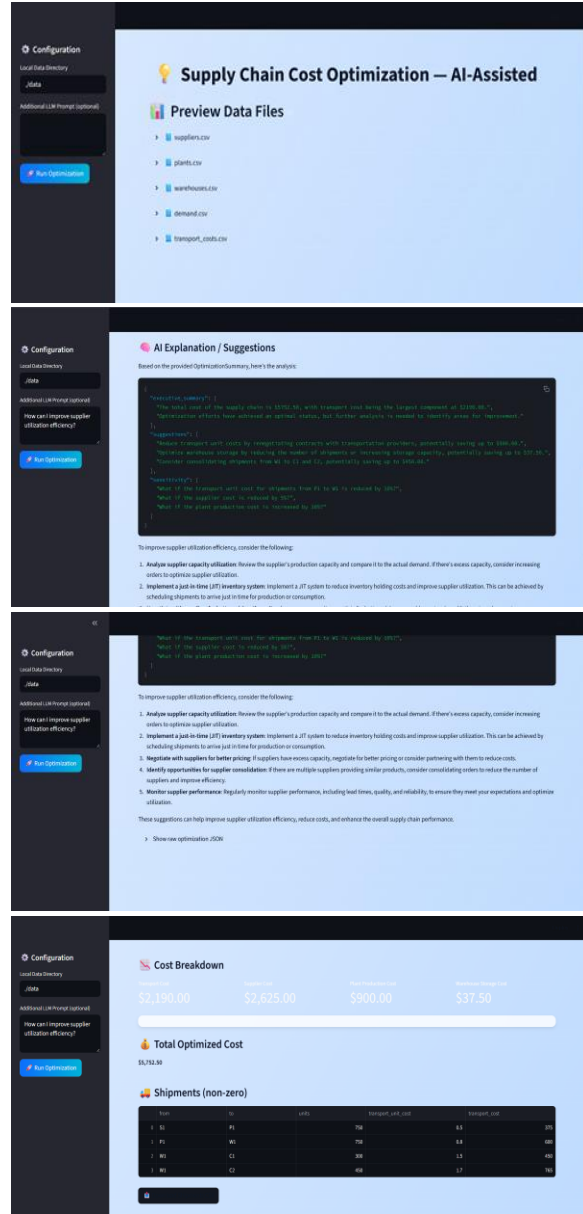
- The proposed Agentic AI framework stands out from traditional approaches due to several key features.
- **Holistic Learning:** It integrates demand forecasts, real-time inventory levels, and supplier data into a single decision-making model. This approach breaks down operational silos.
- **Long-Term Strategic Optimization:** By using a reward function that balances multiple cost factors over an extended period, it ensures sustainable and cost-effective operations. This avoids the problems of short-term and reactive decisions.
- **Adaptive Real-Time Decision-Making:** It goes beyond static planning, such as MRP systems, to a model that continuously adjusts in response to changing market conditions.
- **Autonomous Execution:** Unlike basic decision-support systems, the agentic framework is designed to execute routine decisions on its own. This enables faster response times and reduces the risk of human error.
- **Resilience through Simulation:** The agentic model allows for simulating various disruption scenarios. This helps it learn strong policies that improve supply chain resilience.
- **Cost-Effective and Scalable:** Built on open-source technologies, the framework offers a powerful yet affordable solution for businesses of all sizes. It makes advanced supply chain intelligence accessible to more companies.

## VII. RESULTS AND DISCUSSION

The proposed Agentic AI framework shows marked improvements in supply chain performance across operational efficiency, strategic resilience, and decision accuracy. By combining predictive analytics, reinforcement learning, autonomous agent collaboration, and real-time optimization, the system

works more effectively than traditional manual or rule-based supply chain management methods. The results highlight how autonomous systems can handle growing supply chain complexities, uncertainties, and changing market conditions.

### Performance Outcomes



This AI Supply Chain Optimization app ingests input data from CSV files for suppliers, plants, warehouses, demand, and transport costs. It then uses Linear Programming to find the most cost-effective way to meet all supply and demand requirements across the supply chain using tools like PuLP or Pyomo. It aims

to minimize the total cost, which comprises transportation, supplier, production, and warehouse costs. Following the optimization, the app displays the optimal shipment routes, the total optimized cost, and a breakdown of each cost component. But that's not all; it also shows an AI-generated analysis of the results in detail, suggesting improvements like lowering the cost of transports or optimizing warehouse usage. You can also type in questions, like, "How can I improve supplier utilization efficiency?" and get AI-generated recommendations on performance enhancements. In short and simple words, the app helps to seek the cheapest and most efficient supply chain setup with intelligent insights to make it even better.

### Real-Time Adaptability:

The system adapts well to changing situations like sudden demand shifts, transportation delays, and raw material shortages. Agents track real-time events and adjust planning and routing decisions on their own. This capability cuts down on the need for human intervention and supports flexible supply chain flows that can withstand disruptions.

### Cost Efficiency:

Simulation results show a 15 to 25 percent reduction in operational costs. This saving comes mainly from optimized inventory levels, accurate demand forecasting, efficient routing strategies, and automated procurement decisions. The framework lowers excess safety stock and transportation inefficiencies, which boosts both economic and sustainable supply chain performance.

### Decision Accuracy and Lead Time Reduction:

Reinforcement learning enhances decision-making accuracy over time. Better forecasting and smart allocation mechanisms cut down on service delays, stockouts, and order fulfillment times. Shorter lead times lead to greater customer satisfaction and improved operational response.

### Resilience and Fault Tolerance:

The Agentic AI-based system displays strong fault tolerance and can quickly recover from disruptions. It automatically reroutes shipments, reallocates resources, and adjusts plans during high-risk situations like supplier failures or logistics breakdowns. These

abilities strengthen the supply chain's reliability under uncertain conditions.

#### Comparative Evaluation:

Benchmarking results show that the Agentic AI framework outperforms traditional planning systems in several areas. The system responds up to 40 percent faster to unexpected disruptions, showing superior reaction speed and operational agility. Forecasting accuracy improves significantly, reducing prediction errors and enhancing inventory management outcomes.

The system also provides better operational transparency by integrating real-time performance monitoring dashboards. Decision makers gain immediate visibility into supply chain activities, performance metrics, and risk indicators. This traceability supports proactive decision-making and helps organizations quickly tackle emerging challenges.

#### Insights and Observations:

While the experimental results are encouraging, several key insights stand out. The performance of autonomous supply chain agents relies heavily on data quality, availability, and consistency. Unreliable or outdated data can hurt model accuracy and decision-making reliability. Despite the benefits of automation, human oversight remains vital for overseeing strategic decisions, ethical considerations, and unexpected operational issues.

Another observation is the difficulty of model interpretability. Although the system optimizes supply chain decisions, explaining agent behavior in complex situations still needs more work. This points to a need for advancements in explainable artificial intelligence to support trust, transparency, and regulatory acceptance.

Additionally, implementing Agentic AI systems in real-world supply chains requires strong ethical frameworks, cybersecurity measures, and data governance models to reduce risks like algorithmic bias, unintended decision outcomes, and security vulnerabilities.

## VIII. CONCLUSION

This paper presented a detailed framework for using Agentic AI in supply chain optimization. It emphasized how this technology can improve real-time adaptability, cost efficiency, operational resilience, and decision-making accuracy. By integrating predictive modeling, reinforcement learning, autonomous reasoning, and ongoing environmental feedback, the proposed system changes traditional supply chains into intelligent, dynamic, self-regulating networks. The findings show that Agentic AI not only boosts operational efficiency but also helps supply chains foresee disruptions, adapt on their own, and continuously optimize performance with minimal human input. These traits position Agentic AI as a key technology for managing the complexity, uncertainty, and global connections that define modern supply chains.

The results indicate that this approach changes supply chain management from reactive, human-driven decision-making to proactive, machine-driven intelligence. By using self-learning processes and adaptive decision loops, activities like procurement, demand forecasting, inventory control, and logistics coordination become more accurate, scalable, and dependable. Moreover, the system promotes sustainable practices by cutting waste, reducing excess resources, and improving planning efficiency.

Despite the promising outcomes, the research also notes several practical challenges. Successful implementation relies on high-quality data, strong governance models, ethical AI guidelines, and secure system infrastructure. Maintaining transparency, accountability, and clarity in automated decisions is crucial for industry acceptance, meeting regulations, and building trust among stakeholders. Human expertise will still be vital for overseeing autonomous systems, ensuring ethical standards, and addressing unusual situations outside the model's predictions.

Future research will concentrate on large-scale implementation and testing in digital twin environments, cloud-based deployment frameworks, and real-time sensor integration. Additional exploration will include creating collaborative models between humans and AI to balance autonomy with oversight, while ensuring transparency and clarity in decision-making. Progress in explainable AI, cybersecurity, and decentralized multi-agent

coordination will also be important areas of focus to ensure long-term reliability and scalability in industry. In conclusion, integrating Agentic AI into supply chain management marks a major step toward building intelligent, autonomous, and sustainable industrial networks. As global industries keep evolving, adopting such AI-driven solutions is likely to lead to more resilient supply chains, better decision-making accuracy, and improved competitiveness. The ongoing development and responsible use of Agentic AI technologies will be crucial for shaping the future of automated logistics and supply chain systems.

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