StockSage: Multi-Agent LLM Powered Inventory Management System for Intelligent Supply Chain Optimization

Pranita Pingale[1]; Faiz Asif Shaikh[2]; Om Sanjay Bhongale[3]; Sanvesh Satish Patil[4]

[1,2,3,4]Department of Computer Science and Engineering (Internet of Things and Cyber Security including Blockchain Technology)

[1,2,3,4]SIES Graduate School of Technology, Navi Mumbai, India

Publication Date: 2026/04/02

Abstract: Modern supply chain management systems often suffer from fragmented decision-making where demand forecasting, inventory control, supplier management, and pricing operate as independent processes. This lack of coordination frequently leads to inefficiencies such as stockouts, excess inventory, revenue loss, and poor supplier utilization. To address these challenges, this paper presents StockSage, a multi-agent inventory management system powered by Large Language Models (LLMs). The proposed system employs four specialized agents responsible for forecasting demand, managing inventory levels, selecting optimal suppliers, and recommending pricing strategies. These agents collaborate through a structured two-round coordination protocol that enables cross-functional communication and adaptive decision-making. The system is implemented as a full-stack web application using modern technologies including Next.js, React, TypeScript, Prisma ORM, SQLite, and OpenAI GPT APIs. A Monte Carlo simulation framework is used to evaluate system performance against traditional baseline strategies such as static reorder policies, moving average forecasting, and fixed pricing methods. Experimental results indicate improvements in forecast accuracy, service level, inventory turnover, and revenue optimization. The results demonstrate the potential of coordinated multi-agent LLM systems to provide intelligent, explainable, and scalable decision support for modern inventory and supply chain management.

Keywords: *Multi-Agent Systems; Large Language Models; Inventory Management; Supply Chain Optimization; Demand Forecasting; Decision Explainability; Dynamic Pricing.*

How to Cite: Pranita Pingale; Faiz Asif Shaikh; Om Sanjay Bhongale; Sanvesh Satish Patil (2026) StockSage: Multi-Agent LLM Powered Inventory Management System for Intelligent Supply Chain Optimization. *International Journal of Innovative Science and Research Technology*, 11(3), 2901-2910. https://doi.org/10.38124/ijisrt/26mar1951

I. INTRODUCTION

Inventory management plays a critical role in modern supply chain operations by ensuring that products are available when needed while minimizing storage costs and operational inefficiencies. Organizations rely on effective inventory planning to balance demand fluctuations, supplier lead times, and pricing strategies. However, traditional inventory management systems often rely on static rules, manual configurations, or isolated forecasting models that operate independently without coordination across different supply chain functions. As a result, these systems frequently experience problems such as stockouts, excess inventory, inefficient supplier utilization, and suboptimal pricing decisions.

Recent advancements in artificial intelligence and machine learning have introduced new possibilities for improving inventory planning and supply chain decision-making. Techniques such as statistical forecasting, machine learning models, and reinforcement learning algorithms have demonstrated the ability to analyse historical data and generate improved demand predictions. However, many of these approaches function as black-box systems and often lack explainability, making it difficult for managers to understand the reasoning behind automated decisions. In addition, most traditional approaches treat forecasting, inventory control, supplier management, and pricing as separate modules without effective communication between them.

The emergence of Large Language Models (LLMs) has opened new opportunities for intelligent decision support systems that can reason over complex data and provide human-readable explanations for their outputs. Unlike conventional machine learning models, LLMs can analyse contextual information and generate structured reasoning that is easier for decision-makers to interpret. This capability

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

makes them particularly suitable for applications where transparency and explainability are important.

In this paper, we present StockSage, a multi-agent inventory management system powered by Large Language Models. The proposed system introduces a collaborative architecture in which specialized agents responsible for forecasting, inventory control, supplier selection, and pricing communicate through a structured coordination mechanism. By enabling cross-functional interaction among these agents, the system aims to improve decision quality, adaptability, and transparency in supply chain management. The proposed framework is implemented as a full-stack web application and evaluated using simulation-based experiments to demonstrate its effectiveness compared with traditional inventory management approaches.

II. LITERATURE REVIEW

Recent research has explored the application of artificial intelligence and machine learning techniques in supply chain optimization and inventory management. Several studies have investigated the use of intelligent decision systems to improve forecasting accuracy, inventory control, and pricing strategies.

Researchers have proposed multi-agent inventory management systems where autonomous agents collaborate to optimize stock levels and replenishment decisions. These systems demonstrate improved responsiveness to dynamic market conditions compared to traditional centralized models [1],[2]. Multi-agent architectures allow specialized components to analyze different aspects of supply chain operations while coordinating their decisions to achieve overall efficiency.

The use of machine learning models for demand forecasting has also gained significant attention in recent years. Statistical and machine learning techniques such as regression models, neural networks, and time-series forecasting methods have been widely applied to predict product demand and reduce forecasting errors [3],[4]. Accurate demand forecasting plays a critical role in preventing stockouts and minimizing excess inventory.

Another important area of research focuses on reinforcement learning techniques for inventory optimization and dynamic pricing. Reinforcement learning algorithms can learn optimal replenishment and pricing policies by interacting with simulated environments and continuously improving their decision strategies [5],[6]. These methods have shown promising results in balancing inventory costs and maximizing profit.

Recent advancements in Large Language Models (LLMs) have introduced new possibilities for intelligent decision-support systems. LLMs can analyze large volumes of structured and unstructured data and generate contextual insights through natural language reasoning [7],[8]. Their ability to provide explainable outputs makes them particularly useful for business applications where transparency and interpretability are important.

Researchers have also explored the use of graph-based learning and supply chain network analysis to model supplier relationships and improve supply chain resilience [9],[10]. These approaches help organizations evaluate supplier reliability, lead times, and risk factors more effectively.

Despite these advancements, most existing solutions focus on isolated components of inventory management, such as forecasting, supplier selection, or pricing optimization [11],[12]. There is limited research on integrated systems that combine these components within a unified decision-making framework.

Furthermore, although LLMs have demonstrated strong reasoning capabilities, their integration with multi-agent architectures for coordinated supply chain decision-making is still an emerging research area [13],[14]. This gap highlights the need for intelligent systems that can coordinate multiple business functions while providing explainable recommendations.

The proposed StockSage system addresses these challenges by integrating forecasting, inventory optimization, supplier evaluation, and dynamic pricing into a coordinated multi-agent architecture powered by Large Language Models.

III. PROPOSED SYSTEM

Efficient inventory management requires coordinated decision-making across several operational components including demand forecasting, stock monitoring, supplier evaluation, and pricing optimization. In many existing systems these functions operate independently, which can lead to fragmented decision-making and inefficient resource utilization. For example, forecasting models may predict demand accurately, but without coordination with supplier lead times or pricing strategies, the resulting inventory decisions may still be suboptimal.

To address these limitations, the proposed StockSage system introduces a Large Language Model (LLM) powered multi-agent decision framework designed to support integrated inventory management. The core idea is to represent different supply chain decision processes as specialized intelligent agents that collaborate through a structured communication mechanism. Each agent focuses on a specific operational responsibility while exchanging information with other agents to produce coordinated recommendations.

Recent research has demonstrated that multi-agent decision architectures can significantly improve responsiveness and adaptability in supply chain environments. For example, studies on LLM-based inventory agents have shown that autonomous agents can generate interpretable recommendations and adapt to changing demand conditions without extensive retraining . Building on these ideas, the StockSage system integrates forecasting, inventory control, supplier analysis, and pricing decisions within a unified framework.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

➢ *System Architecture*

The proposed system follows a modular architecture consisting of four specialized agents connected through a coordination layer. Each agent processes relevant data and generates intermediate outputs that influence the decisions of other agents in the system. This architecture allows the system to distribute analytical tasks across multiple components while maintaining overall decision consistency.

The primary input to the system includes historical sales data, product information, and supplier records. These data sources are first processed in a preprocessing stage where relevant attributes such as sales trends, seasonal variations, and supplier performance indicators are extracted. The processed data is then provided to the multi-agent decision framework.

The architecture enables each agent to analyse relevant operational information while maintaining communication with other agents to ensure consistent decision outcomes.

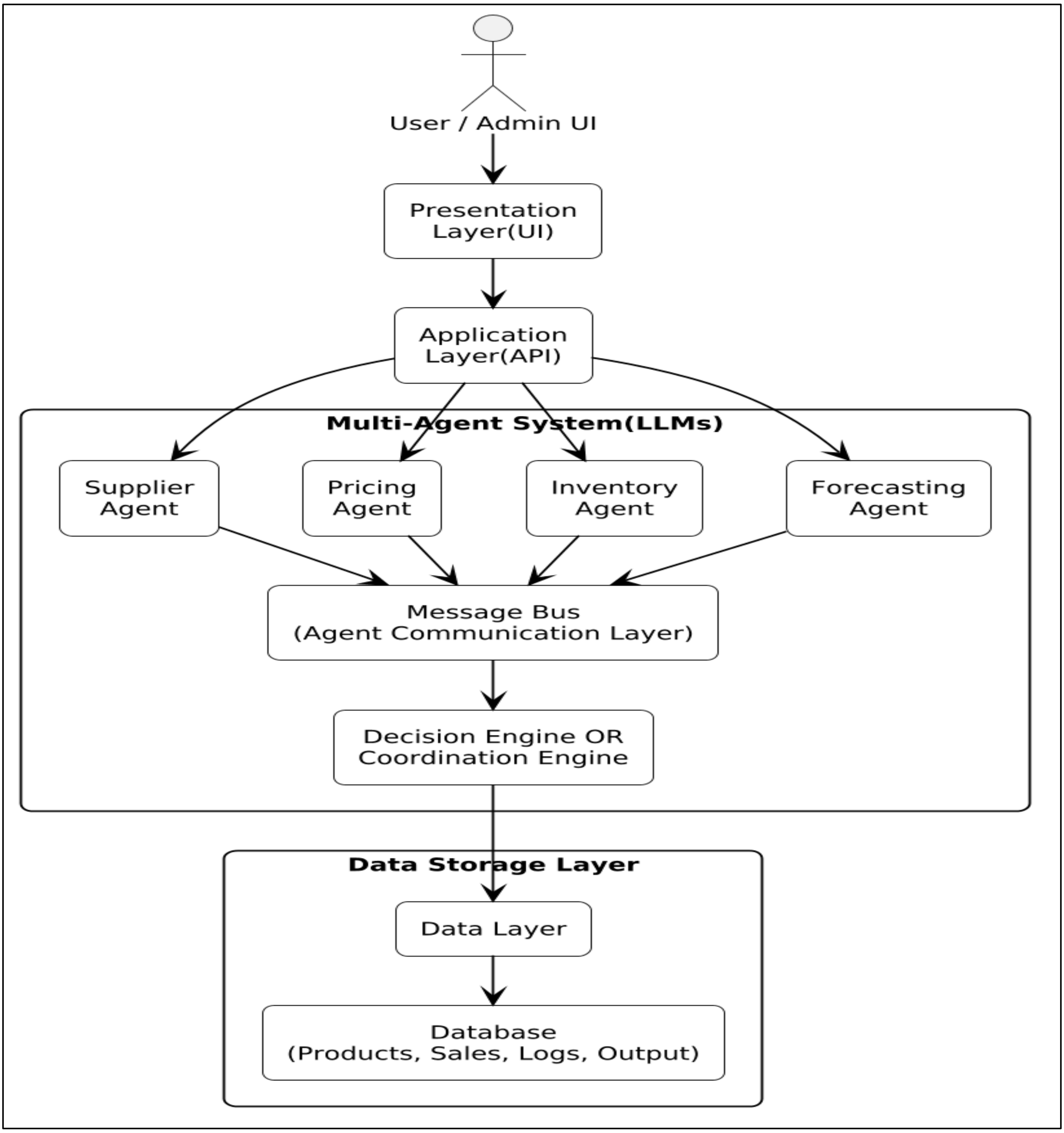

Fig 1 System Architecture

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

➢ *Functional Design of System Agents*

Each agent within the StockSage framework performs a specialized task within the supply chain decision pipeline. By distributing responsibilities across multiple agents, the system can analyse different aspects of supply chain operations simultaneously while maintaining a coordinated decision-making process. The key responsibilities of each agent are summarized in Table 1.

Table 1 Functional Responsibilities of StockSage Agents

Agent	Main Function	Input Data	Output
Forecasting Agent	Predict future demand using historical trends and seasonal patterns	Historical sales data, product records	Demand forecast, confidence level
Inventory Agent	Determine optimal reorder quantities and safety stock levels	Forecast results, current inventory levels	Reorder recommendation, stock alerts
Supplier Agent	Evaluate suppliers based on lead time, reliability, and cost	Supplier database, delivery history	Supplier ranking and selection
Pricing Agent	Adjust product prices based on demand and inventory status	Demand forecast, inventory data	Dynamic pricing recommendations

➢ *Multi-Agent Decision Coordination*

One of the key features of the proposed system is the ability of agents to communicate and refine their decisions through a structured coordination mechanism. Unlike traditional systems where decisions are made independently, the StockSage architecture allows agents to exchange contextual information and adjust their outputs accordingly.

For example, if the forecasting agent predicts an increase in demand for a particular product, the inventory agent may increase reorder quantities to prevent potential stockouts. Similarly, the pricing agent may recommend slight price adjustments to balance demand and inventory availability.

This collaborative decision-making process helps ensure that inventory planning, supplier selection, and pricing strategies are aligned with predicted demand patterns and operational constraints.

➢ *Integration of Large Language Models*

Large Language Models play a central role in the proposed system by enabling contextual reasoning and explainable decision support. Unlike traditional machine learning models that operate primarily on numerical data, LLMs can interpret structured and semi-structured information and generate human-readable recommendations.

In the StockSage system, the LLM acts as a reasoning layer that interprets outputs generated by individual agents and produces coordinated decision suggestions. The LLM also provides explanatory outputs that help users understand the reasoning behind inventory recommendations.

This feature is particularly useful for business decision-makers who require transparency in automated decision systems. The ability of LLMs to generate interpretable insights allows the system to serve as a decision-support tool rather than a fully automated black-box model.

➢ *System Workflow*

The overall workflow of the proposed system can be summarized in the following stages:

- *Data Preparation:*

  Historical sales records, product details, and supplier information are collected and processed to extract relevant attributes.

- *Demand Forecasting:*

  The forecasting agent analyses historical data to estimate future product demand.

- *Inventory Optimization:*

  The inventory agent determines reorder quantities and safety stock levels based on predicted demand.

- *Supplier Evaluation:*

  The supplier agent identifies the most reliable suppliers based on delivery performance and lead times.

- *Dynamic Pricing:*

  The pricing agent recommends pricing adjustments based on demand conditions and inventory availability.

- *Decision Integration:*

  The LLM-based reasoning layer combines outputs from all agents and generates final recommendations.

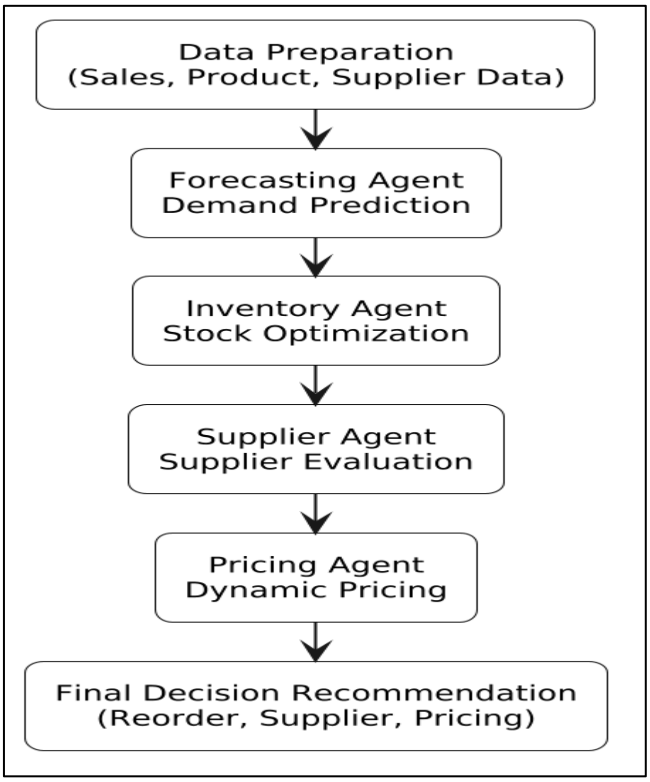

Fig 2 System Workflow

Through this workflow, the StockSage system enables coordinated supply chain decision-making while maintaining transparency and adaptability.

IV. METHODOLOGY

The methodology adopted in this research focuses on evaluating the effectiveness of the proposed StockSage multi-agent inventory management framework through a structured decision pipeline and simulation-based analysis. The methodology integrates data preparation, agent-based reasoning, coordinated decision generation, and performance evaluation. This approach allows the system to analyse supply chain information from multiple perspectives while producing consistent inventory recommendations.

The overall workflow of the system consists of four primary stages: data preprocessing, agent-based analysis, inter-agent coordination, and performance evaluation. These stages collectively enable the system to simulate realistic inventory decision scenarios and evaluate the effectiveness of the proposed multi-agent architecture.

➢ *Data Preparation and Processing*

The first stage of the methodology involves preparing the dataset used for simulation and analysis. Historical sales records, product attributes, and supplier information are collected and organized into structured datasets. These datasets form the primary inputs for the forecasting and decision-making components of the system.

The preprocessing stage includes several operations such as cleaning missing values, normalizing numerical attributes, and extracting relevant time-series features from historical sales data. These features include demand trends, seasonal patterns, and moving average statistics that are used by the forecasting agent to estimate future demand.

Supplier information is also processed to extract key performance indicators such as average delivery time, supplier reliability, and procurement cost. These attributes are later used by the supplier evaluation agent during vendor selection.

Proper data preparation ensures that the decision-making agents operate on consistent and reliable input data, which is essential for accurate simulation results.

➢ *Multi-Agent Decision Framework*

The proposed system employs a multi-agent architecture where each agent performs a specialized analytical task. The agents operate sequentially while sharing intermediate outputs through a coordination layer. This design allows each component to focus on a specific operational objective while contributing to the overall system decision.

The decision framework consists of four primary agents:

- Demand Forecasting Agent
- Inventory Optimization Agent
- Supplier Evaluation Agent
- Dynamic Pricing Agent

Each agent receives input data from the previous stage and produces outputs that influence subsequent decisions. The modular design of the framework allows individual agents to be improved or replaced without affecting the overall system architecture.

➢ *Two-Round Coordination Protocol*

A key feature of the methodology is the two-round coordination protocol used for generating optimized decisions. This protocol enables agents to refine their outputs through collaboration rather than operating independently.

- *Round 1: Independent Decision Generation*

In the first round, each agent performs an independent analysis based on the available input data. For instance, the forecasting agent predicts product demand using historical sales patterns, while the inventory agent estimates reorder quantities based on forecasted demand and current stock levels.

At this stage, the agents produce preliminary recommendations without considering the outputs of other agents.

- *Round 2: Coordinated Decision Refinement*

In the second round, agents exchange their outputs and update their decisions accordingly. This communication process allows the system to incorporate contextual information into each decision stage.

For example, if the supplier agent identifies long lead times for a selected vendor, the inventory agent may increase the reorder quantity to prevent stock shortages. Similarly,

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

pricing decisions may be adjusted if predicted demand significantly exceeds available inventory.

This collaborative reasoning process allows the system to produce more balanced and realistic inventory decisions.

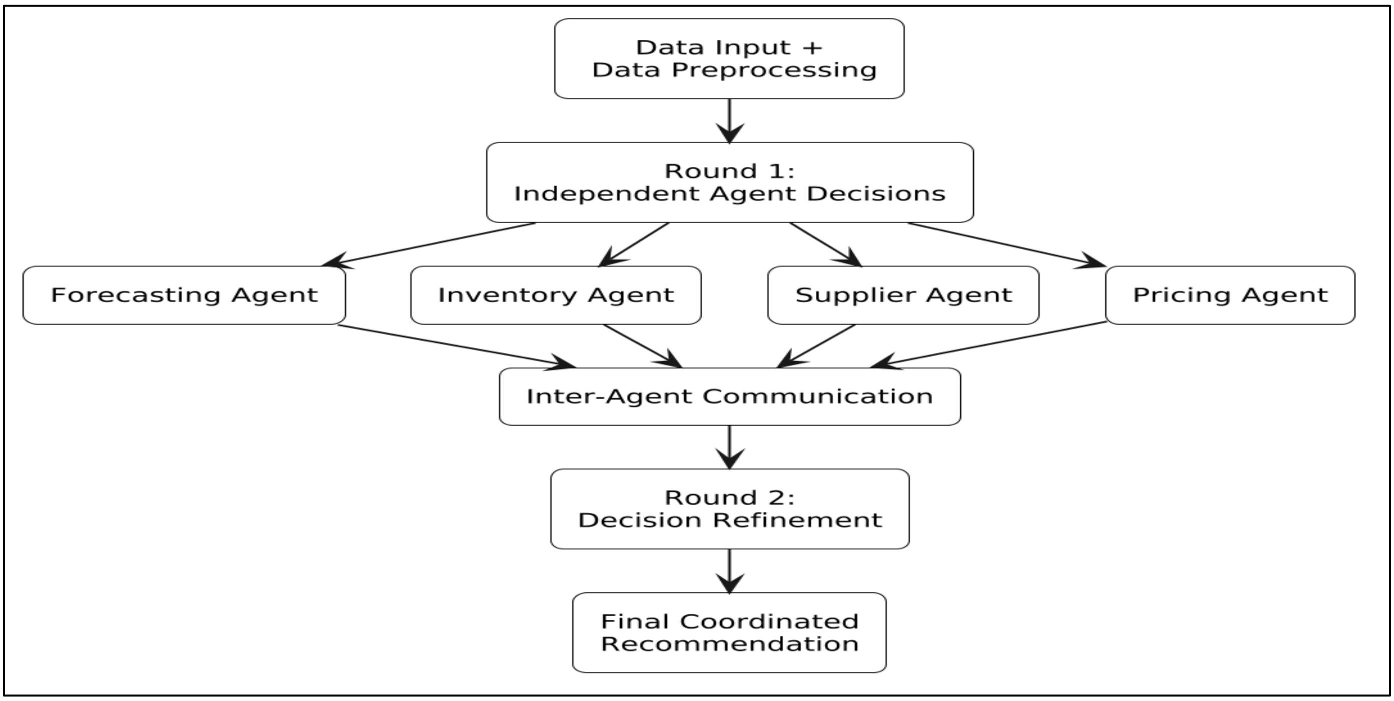

Fig 3 Multi-Agent Coordination Workflow

- *Evaluation Methodology*

To evaluate the effectiveness of the proposed StockSage framework, simulation experiments are conducted using historical inventory data and generated demand scenarios. The system's recommendations are compared with traditional inventory management approaches such as static reorder rules and simple forecasting methods.

The evaluation focuses on measuring improvements in forecasting accuracy, inventory utilization, and financial performance.

Several performance metrics are used to assess system effectiveness.

Table 2 Forecast Accuracy Metrics

Metric	Formula	Description
MAE (Mean Absolute Error)	$\frac{1}{n}\sum \mid actual - predicted \mid$	Measures the average absolute difference between actual and predicted values, indicating overall forecast accuracy
RMSE (Root Mean Square Error)	$\sqrt{\frac{1}{n}\sum (actual - predicted)^2}$	Penalizes larger errors more heavily, making it sensitive to outliers in predictions
MAPE (Mean Absolute Percentage Error)	$\frac{1}{n}\sum \left(\frac{actual - predicted}{actual}\right) \times 100$	Expresses forecast error as a percentage, providing relative accuracy independent of scale

Table 3 Performance Metrics

Metric	Description
Days of Stock	Average number of days the current inventory can satisfy demand based on recent sales rates.
Holding Cost	Cost incurred for storing inventory over time, typically calculated as a percentage of product cost per year.
Excess Inventory	Amount of stock exceeding expected demand levels, indicating potential overstock situations.
Stockout Rate	Percentage of days when product demand exceeds available inventory.
Inventory Turnover Rate	Number of times inventory is sold and replenished during a given period.
Profit Margin	Percentage of revenue retained as profit after deducting cost of goods sold.
Total Profit	Total financial gain obtained from sales after subtracting all inventory procurement costs.
Total Revenue	Total income generated from product sales during the simulation period.
Service Level	Percentage of customer demand that is successfully fulfilled without stock shortages.
Forecast Accuracy	Degree to which predicted demand matches actual demand values during evaluation.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

These metrics provide a comprehensive evaluation of how well the proposed system improves supply chain performance.

To provide an overall performance measure, a composite score is computed by combining forecasting accuracy, inventory performance, and financial performance metrics using weighted contributions.

$$Composite\ Score = Forecast\ Score\ \times 0.25 + Inventory\ Score \times 0.40 + Pricing\ Score \times 0.35$$

This weighted formulation ensures that inventory efficiency receives greater emphasis while still considering forecasting accuracy and financial outcomes.

➢ *Simulation and Experimental Procedure*

The evaluation process is conducted through a simulation-based environment where different demand scenarios are generated using historical data patterns. Each simulation run represents a predefined planning horizon in which inventory decisions are generated by the system and compared against baseline approaches.

The experimental procedure involves the following steps:

- Load historical sales and supplier datasets.
- Generate demand forecasts using the forecasting agent.
- Compute reorder quantities using the inventory agent.
- Select suppliers based on delivery performance and cost metrics.
- Apply dynamic pricing adjustments based on demand conditions.
- Measure performance metrics for each simulation run.

Multiple simulation runs are conducted to ensure consistent results and reduce the impact of random demand fluctuations.

V. EXPERIMENTAL SETUP

This section describes the experimental configuration used to evaluate the performance of the proposed StockSage multi-agent inventory management system. The experiments were designed to simulate realistic supply chain conditions and compare the proposed framework with traditional inventory management approaches.

➢ *Dataset Description*

The experimental evaluation was conducted using a dataset containing product sales records, inventory information, and supplier data. The dataset includes approximately 3600 product instances, representing a diverse set of products with varying demand patterns and supplier characteristics.

The dataset contains attributes such as product identifiers, historical sales values, supplier lead times, and pricing information. These attributes were used to simulate demand forecasting, inventory planning, supplier evaluation, and pricing decisions within the proposed system.

Historical sales data was used to generate demand forecasts, while supplier records were used to evaluate delivery performance and lead time reliability.

➢ *Simulation Environment*

The evaluation of the proposed system was performed using a simulation-based decision environment. The simulation represents a typical inventory planning horizon in which product demand, stock levels, and supplier performance are continuously evaluated.

During each simulation cycle, the system performs the following steps:

- Generate demand forecasts using the forecasting agent.
- Compute optimal reorder quantities using the inventory agent.
- Select appropriate suppliers based on lead time and reliability.
- Adjust product prices based on demand and inventory conditions.
- Record operational and financial performance metrics.

This simulation process allows the system to evaluate the effectiveness of coordinated multi-agent decision-making under dynamic demand conditions.

The key parameters used in the simulation environment are summarized in Table 4.

Table 4 Simulation Parameters

Parameter	Value	Description
Number of Products	20	Distinct products used in simulation
Historical Sales Period	180 days	Historical demand data used for forecasting
Number of Suppliers	8	Suppliers evaluated for procurement decisions
Simulation Horizon	90 days	Duration of simulated operational cycles
Inventory Review Interval	Daily	Frequency of stock evaluation
Demand Variability	Moderate	Simulated variation in product demand
Pricing Strategy	Dynamic	Prices adjusted based on demand and inventory levels
Evaluation Runs	Multiple runs	Simulations repeated to ensure consistent results

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

VI. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed StockSage multi-agent inventory management system. The evaluation was conducted using simulation experiments based on historical demand patterns and supplier characteristics. The results were analysed across three major dimensions: forecasting accuracy, inventory efficiency, and financial performance.

➤ *Overall Performance Comparison*

The experimental results demonstrate that the proposed multi-agent LLM-based framework significantly outperforms traditional inventory management methods. The system achieved a composite performance score of 90.1, which represents the highest performance among all evaluated approaches.

In comparison, traditional static rule-based inventory systems achieved a score of 72.6, while fixed pricing strategies achieved a score of 70.8. The moving average forecasting approach produced the lowest performance score of 58.7, highlighting the limitations of relying solely on basic statistical forecasting techniques.

Table 5 Composite Performance Score Comparison

Method	Composite Score
Moving Average Forecasting	58.7
Fixed Pricing Strategy	70.8
Static Reorder Rules	72.6
Multi-Agent LLM (StockSage)	90.1

➤ *Forecasting Performance*

The forecasting agent predicts product demand using historical sales patterns, trend analysis, and seasonality factors. The performance of the forecasting module was evaluated using standard error metrics such as MAE, RMSE, and MAPE. Compared to a moving-average baseline, the forecasting agent demonstrated improved prediction stability and lower average error values.

The results indicate that the forecasting agent is able to capture seasonal fluctuations and demand spikes more effectively than simple statistical models. Improved forecasting accuracy plays a critical role in inventory planning, as more reliable demand predictions enable the system to maintain optimal stock levels and reduce the risk of both overstocking and stock shortages.

➤ *Inventory Performance*

Inventory efficiency was evaluated using operational metrics such as stockout rate, service level, holding cost, and days of stock coverage. The multi-agent coordination mechanism enables the system to dynamically adjust reorder quantities based on demand forecasts and supplier lead times.

The experimental results show a noticeable reduction in stockout events compared to traditional rule-based inventory approaches. At the same time, the system avoids excessive inventory accumulation by adjusting reorder quantities and pricing strategies when excess stock is detected.

This coordinated decision-making process allows the system to maintain a balance between inventory availability and cost efficiency. As a result, the system achieves higher service levels while maintaining lower average holding costs.

➤ *Financial Performance*

The financial impact of the proposed system was evaluated using metrics such as total revenue, total profit, profit margin, and inventory turnover rate. The pricing agent dynamically adjusts product prices based on demand forecasts and inventory conditions.

Simulation results indicate that the use of dynamic pricing strategies helps increase total revenue while maintaining healthy profit margins. When demand increases, the pricing agent recommends moderate price increases to maximize revenue. Conversely, when excess inventory is detected, the system recommends promotional pricing strategies to accelerate product turnover.

This dynamic approach improves overall financial performance while simultaneously supporting inventory optimization.

➤ *Comparative Analysis with Baseline Methods*

To better understand the benefits of the proposed system, the results were compared with traditional baseline approaches including static reorder rules, moving average forecasting, and fixed pricing strategies.

Table 6 summarizes the key differences between conventional inventory systems and the proposed StockSage framework.

The comparison highlights that the proposed system provides improved adaptability and better integration between forecasting, inventory management, and pricing decisions.

Table 6 Comparative Analysis of Inventory Management Approaches

Feature	Traditional Systems	StockSage System
Forecasting	Moving average / static models	LLM-based adaptive forecasting
Pricing	Fixed pricing strategies	Dynamic pricing based on demand
Coordination	Independent modules	Multi-agent coordination
Decision Transparency	Limited	Explainable AI reasoning
Adaptability	Low	High

➢ *Impact of Multi-Agent Coordination*

A key contribution of the proposed system is the use of multi-agent coordination for supply chain decision-making. In the first round of analysis, each agent independently generates recommendations based on available data. During the second round, agents exchange information and revise their decisions accordingly.

This two-stage coordination process significantly improves decision quality. For example, if the inventory agent identifies excess stock levels, the pricing agent may lower prices to increase sales and reduce holding costs. Similarly, when forecasted demand increases, the inventory agent may increase reorder quantities to avoid potential stockouts.

These interactions enable the system to respond more effectively to dynamic supply chain conditions.

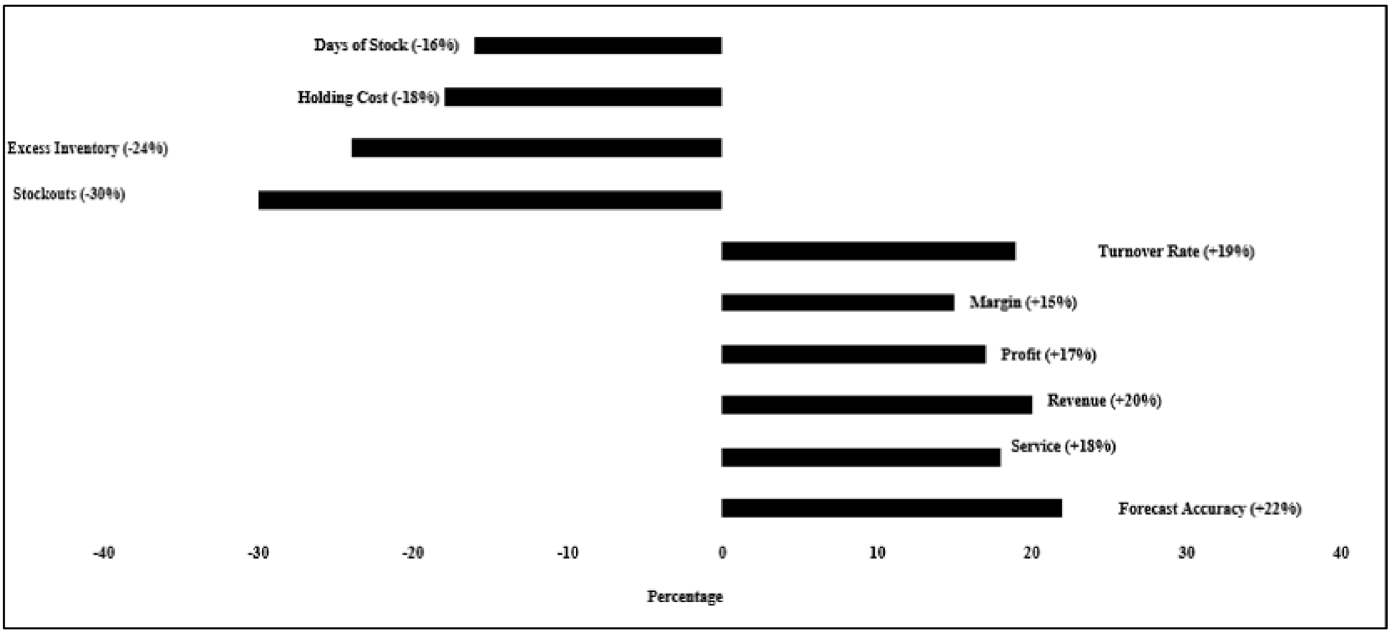

Fig 4 Impact of Multi-Agent Coordination

➢ *Key Observations*

Several observations can be derived from the experimental results:

- Multi-agent coordination improves overall decision quality by allowing agents to incorporate cross-functional insights.
- The forecasting agent significantly reduces prediction errors compared to traditional statistical models.
- Dynamic pricing strategies increase revenue while preventing inventory stagnation.
- Explainable decision outputs improve transparency and make the system more suitable for real-world adoption.

Overall, the experimental results demonstrate that the proposed StockSage system provides more adaptive, coordinated, and transparent inventory management compared to conventional rule-based approaches.

While the results demonstrate strong performance improvements, the current evaluation is based on simulated data and may require further validation using real-world supply chain datasets.

VII. CONCLUSION

This paper presented StockSage, an intelligent multi-agent inventory management framework designed to improve supply chain decision-making through coordinated forecasting, inventory optimization, supplier evaluation, and dynamic pricing. The proposed architecture enables specialized agents to independently analyse different operational aspects and refine their decisions through inter-agent communication. This collaborative reasoning process allows the system to incorporate demand patterns, inventory constraints, and supplier characteristics while generating balanced and context-aware recommendations.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1951

The performance of the system was evaluated using simulation experiments covering approximately 3600 product instances and compared with conventional approaches such as static reorder rules, moving average forecasting, and fixed pricing strategies. The experimental results demonstrate that the proposed system significantly improves overall supply chain performance. In particular, the system achieved a composite performance score of 90.1, outperforming static rule-based systems (72.6), fixed pricing approaches (70.8), and moving average forecasting methods (58.7). These findings indicate that coordinated multi-agent decision-making can substantially enhance forecasting reliability, inventory efficiency, and financial outcomes in modern inventory management systems.

FUTURE WORK

Future work will focus on extending the proposed StockSage framework to support real-time enterprise data integration and deployment in practical supply chain environments. Incorporating advanced learning techniques such as reinforcement learning for adaptive inventory policies and graph-based models for supplier network analysis could further enhance decision accuracy and resilience. Additionally, evaluating the system using larger real-world datasets and multi-echelon supply chain scenarios would provide deeper insights into the scalability and practical impact of the proposed multi-agent approach.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to Prof. Pranita Pingale for her valuable guidance, insightful discussions, and continuous support throughout the course of this research. Her expertise and constructive feedback significantly contributed to shaping the methodology and improving the overall quality of this work.

The authors also acknowledge the support provided by the Department of Computer Science and Engineering (Internet of Things and Cyber Security including Blockchain Technology), SIES Graduate School of Technology, Navi Mumbai, for offering the necessary academic environment and resources to carry out this research.

Finally, the authors appreciate the contributions of peers and colleagues whose discussions and feedback helped refine the ideas presented in this paper.

REFERENCES

[1]. Y. Wang, J. Liu, and H. Zhang, “InvAgent: a large language model based multi-agent system for inventory management in supply chains,” arXiv preprint, arXiv:2503.07231, 2025.

[2]. Z. Xu, L. Chen, and Q. Huang, “Large language models for UNSPSC item categorization in industrial supply chains,” arXiv preprint, arXiv:2407.11384, 2024.

[3]. X. Li, Y. Zhao, and P. Sun, “Large language models for industrial automation: event-driven decision systems,” arXiv preprint, 2025.

[4]. R. Huang, S. Wang, and T. Li, “Resource-efficient large language models for industrial applications: techniques and challenges,” arXiv preprint, 2025.

[5]. J. Gijsbrechts, R. Boute, and J. Van Mieghem, “Learning-based inventory control: a review of machine learning and reinforcement learning methods,” European Journal of Operational Research, 2024.

[6]. M. Sadeghi and Q. Zhao, “Deep reinforcement learning for vendor managed inventory in semiconductor supply chains,” in Proceedings of the Winter Simulation Conference, 2023.

[7]. Y. Xu, H. Li, and X. Chen, “Deep reinforcement learning for inventory control under random demand and lead times,” Computers & Industrial Engineering, 2024.

[8]. K. Zhang, L. Wang, and D. Li, “Deep reinforcement learning for dynamic pricing and ordering policies in perishable inventory management,” 2024.

[9]. S. Narayanan, R. Gupta, and A. Kumar, “Multi-echelon inventory optimization using deep reinforcement learning,” 2023.

[10]. J. Ahn, S. Lee, and D. Kim, “Federated graph neural networks for supply chain link prediction,” arXiv preprint, 2025.

[11]. R. Goyal, P. Sharma, and M. Gupta, “Graph learning in supply networks: a survey of graph neural network approaches,” arXiv preprint, 2025.

[12]. Y. Qiu, Z. Chen, and H. Wang, “Artificial intelligence driven green supply chain management and sustainability performance,” 2024.

[13]. F. Lin, Y. Chen, and T. Zhang, “Artificial intelligence and metaverse applications in supply chain management,” 2023.

[14]. S. Saghafian and M. Van Oyen, “Artificial intelligence in supply chain optimization: opportunities and challenges,” IEEE Transactions on Engineering Management, 2024.