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AI-DRIVEN DEMAND FORECASTING AND INVENTORY OPTIMIZATION IN SUPPLY CHAIN MANAGEMENT: ENHANCING EFFICIENCY AND REDUCING OPERATIONAL COSTS

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Abstract

Background: *In this study, the increased complexity of today supply chains and explain why conventional forecasting and inventory management techniques are inadequate in today's dynamic and uncertain market conditions. As globalization and data increase, AI has become a gamechanger in delivering better demand forecasting and inventory management, in turn driving a better operation and cost savings.*

Objectives: *This study seeks to assess the performance of AI-based demand forecasting models combined with inventory optimization methods on improving the overall performance of the supply chain.*

Methods: *A quantitative, data-driven methodology was employed, and secondary data were used, including historical demand, inventory levels, and other external data that included seasonality and economic indicators. Demand forecasting models: Advanced machine learning and deep learning models such as Long Short-Term Memory (LSTM), Random Forest and Gradient Boosting were used for demand forecasting. The results of the forecasts were fed into an inventory optimization system using reinforcement learning for dynamic decision-making. Standard deviations like Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to measure the model's performance along with cost-performance analysis.*

Results: *The accuracy of the prediction is significantly higher in AI-based models, especially the LSTM model, than the traditional models, which decreases the errors of the prediction and enhances its responsiveness. AI-powered inventory optimization resulted in significant savings on inventory holding and shortage/cost of order, and improved service levels and inventory stockout rates. The use of external data had yet further improved predictive performance.*

Conclusion: *AI-powered demand forecasting and inventory optimization offer a solid solution to improve the efficiency of the supply chain, make intelligent decisions and minimize operational costs.*

Keywords: Artificial Intelligence, Demand Forecasting, Inventory Optimization, Supply Chain Management, Machine Learning

1. Introduction

Global supply chains in the digital economy have become extremely dynamic, complex, and uncertain, thereby increasing the demand for intelligent systems that can deal with uncertainty, complexity, and dynamic market behaviours (Mitta, 2023; Nweje & Taiwo, 2025). Most supply chain models are built around deterministic forecasts and linear methods are, to a large extent, unable to account for nonlinear demand and stochastic variability prevalent in today's markets. In the classical demand forecasting problem, the forecasting

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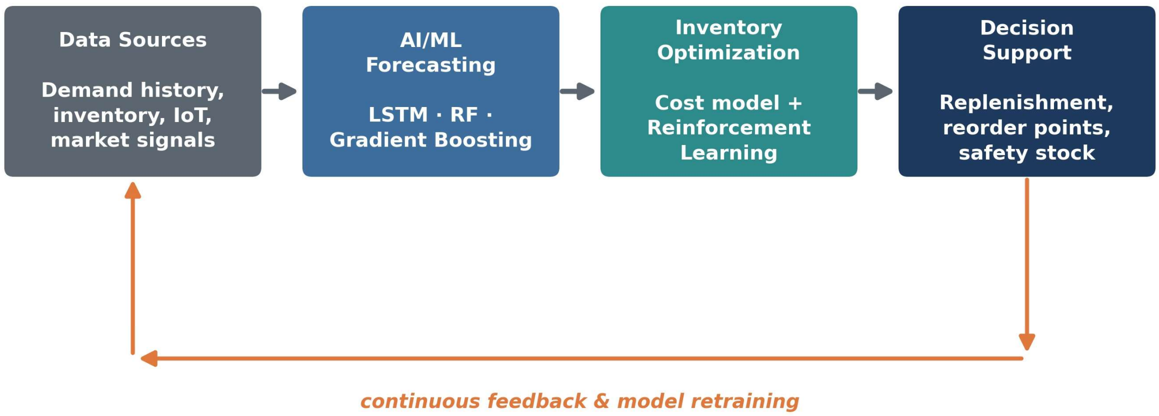
problem is expressed as D^t = f(Xt). Where, D^t is the demand forecast at time t and Xt are the exogenous variables and history. These models often have large prediction errors, however, because they are not very flexible and don't ingest all the data streams in real time (Douaioui et al., 2024; Sajja et al., 2025).

Figure 1

AI-driven supply chain framework.



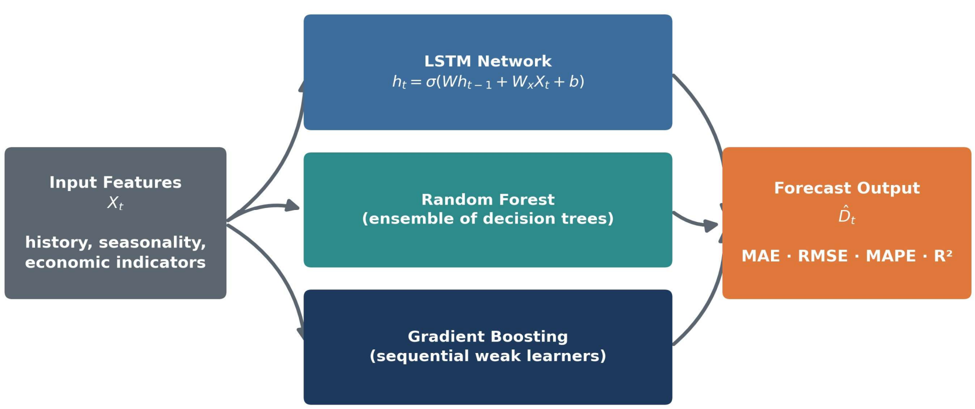
This new paradigm of Artificial Intelligence (AI), especially Machine learning (ML) and Deep learning (DL), has revolutionized the ability to improve the accuracy of forecasting and make it efficient *(Figure 1)*. With the aid of Artificial Intelligence (AI) system models like Long Short-Term Memory (LSTM) networks and gradient boosting algorithms, nonlinear function approximation f:Rn→R can be used to learn complex temporal aspects of demand signals (Pasupuleti et al., 2024; Kagalwala et al., 2025). The recent studies show that hybrid models such as Light GBM-PSO-LSTM lead to more accurate forecasting and a better improvement in inventory turnover than the traditional statistical models. These models take into account temporal and external characteristics and thus are more robust in their predictions and have less variability in their prediction errors (Kaul & Khurana, 2022; Verma, 2024).

One such area that is fundamental for a reduction in the overall cost of the supply chain is demand forecasting, which can be defined as the strategy used to optimise inventories (Patil, 2024; Islam et al., 2024). Normally, the inventory control problem is expressed as a cost minimization function:

min TC=∑t=1T(ChIt+CsSt+CoOt)

Figure 2

Demand forecasting model architecture



TC = total cost, Ch = holding cost, Cs = shortage cost, Co = ordering cost, It = inventory level, St = shortage quantity and Ot = order quantity. AI optimizes this process by adapting decision variables in real

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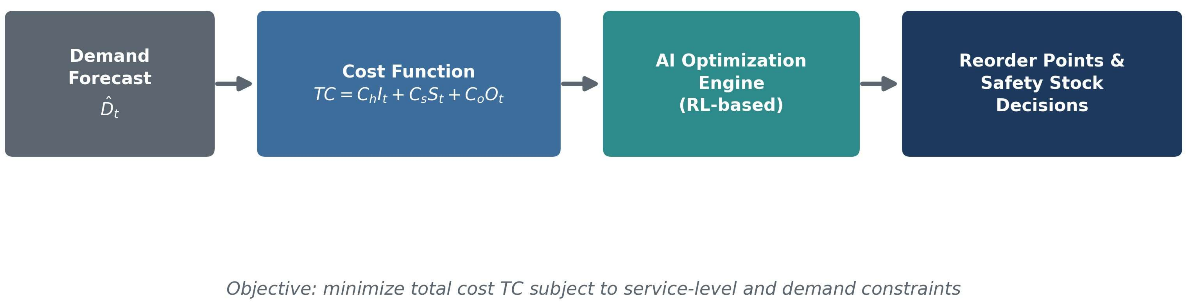
time, based on predictive insights and, consequently, reorder points and safety stock levels *(Figure 2)*. Empirical results show that the inventory cost can be drastically lowered without compromising the high level of service using AI-based systems.

AI's role in supply chain systems also facilitates multi-echelon inventory optimization, coordinating inventory decisions at various points in the supply chain. Complex supply chains exhibit interdependencies between nodes, which are now being modelled using graph-based and probabilistic models like Graph Neural Networks (GNNs). The models calculate imbalances in supply and demand with a probabilistic function, thus enhancing the overall resilience and synchronization of the system. These strategies illustrate how a move from single optimization to network intelligence has been made (Ghodake et al., 2024).

Figure 3

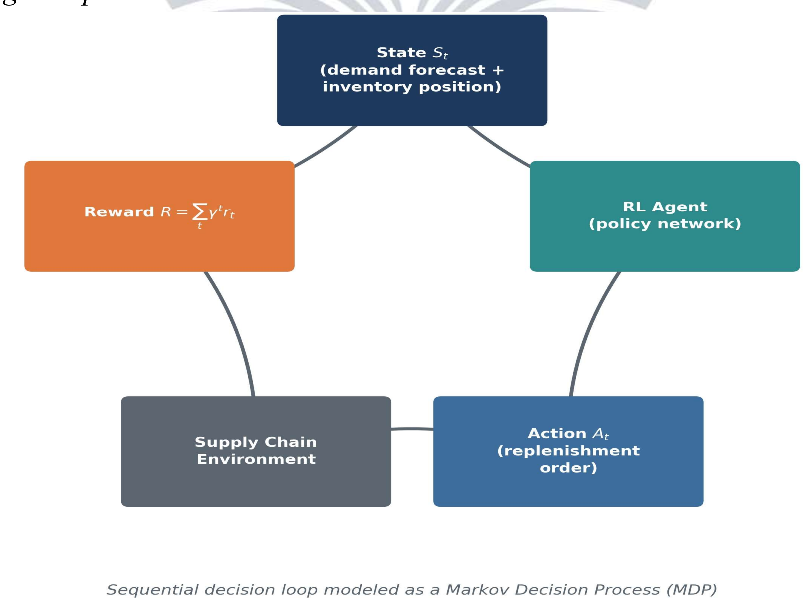
Inventory Optimization Strategies.



Beyond predicting the accuracy Ayub et al. (2024), AI also helps with real-time demand sensing by leveraging the integration of real-time data from IoT devices, point-of-sale systems, and external market indicators *(Figure 3)*. This results in adaptive forecasting models that take the form of D^t+1=f(Dt,Zt,θt). Where, Zt represents real-time contextual information and θt represents parameters that are dynamically updated. It has been demonstrated that the addition of contextual factors, like seasonality, holidays and economic indicators is very beneficial for forecasting performance and mean absolute error (MAE).

Figure 4

AI forecasting feeding RL optimization.



AI isn't just about prediction; it's also about systems that combine demand forecasting with inventory and logistics optimization, providing a powerful tool for making informed decisions. Reinforcement learning

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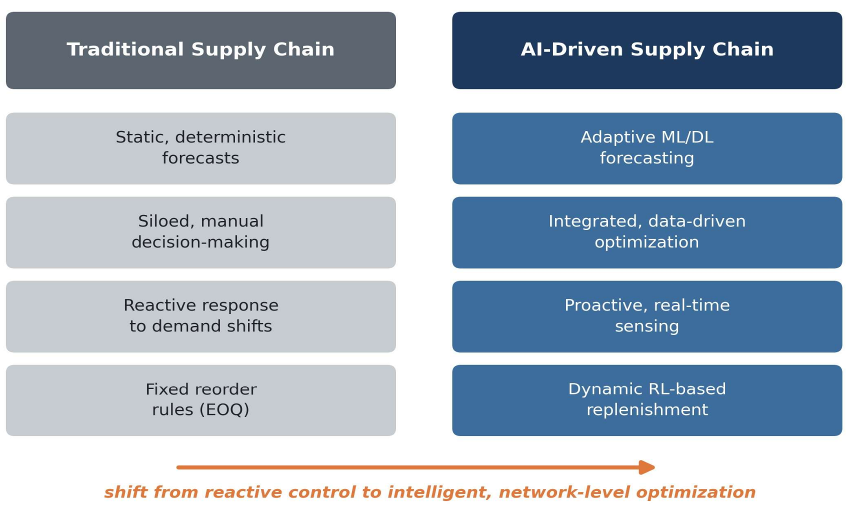
(RL) frameworks model the decisions in the supply chain as a Markov Decision Process (MDP) with the goal of maximizing the cumulative reward R=∑t=0∞γtrt. These systems are able to learn optimal policies for inventory replenishment and distribution under uncertainty, thus improving efficiency and minimizing operational costs *(Figure 4)*. These are examples of how predictive analytics and prescriptive optimization have come together in today's supply chain.

While these progressions have been achieved, there are still challenges to overcome in deploying AI-based systems, such as data heterogeneity, model interpretability, and integration with existing systems (Ayub et al., 2024). The traditional forecasting methods are unable to handle high-dimensional and large-scale data, which results in inefficiency and higher operational costs. Furthermore, the lack of standardized processes and practices for the adoption of AI in value chains restricts the scalability and widespread application of AI technologies. The systematic reviews emphasize that the success of AI applications relies on the quality of the data, computational power, and organizational preparedness.

Current studies are increasingly focused on architectures of hybrid AI, which include statistical, machine learning, and optimization methods to realize better performance. A combination of deep learning models with optimization algorithms like BO-CNN-LSTM has been shown to achieve better performance in spatiotemporal demand modelling and inventory management. These developments highlight the shift to intelligent, autonomous, self-learning and continuous improvement supply chains.

Figure 5
Supply Chain Diagram



Although there is proven value in the use of AI-based demand forecasting and inventory optimization, there are still many organizations that use the traditional approach that cannot keep up with the dynamic nature of demand and cost inefficiencies (Nweje & Taiwo, 2025). The issue highlighted in this study is thus the lack of effective utilization of advanced AI levels in the implementation of the supply chain operations *(Figure 5)*. The impact of this research is that it could offer a full picture of AI-based systems to enhance forecast accuracy and optimize inventory management to minimize operational expenses. This research aims to explore and assess AI-driven demand forecasting and inventory optimization methods to improve the efficiency and cost-effectiveness of supply chains.

2. Literature Review

2.1 Traditional Demand Forecasting Approaches

Traditional demand forecasting methods have long been the cornerstone of supply chain planning. These approaches typically rely on statistical techniques such as moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA) models. The classical demand forecasting problem is expressed as D^t = f(Xt), where D^t is the demand forecast at time t and Xt are the exogenous variables and history. However, these models often have large prediction errors because they lack flexibility and cannot ingest all data streams in real time (Douaioui et al., 2024; Sajja et al., 2025). The deterministic nature of these models makes them inadequate for capturing nonlinear demand patterns and stochastic variability prevalent in today's markets (Mitta, 2023; Nweje & Taiwo, 2025).

2.2 Artificial Intelligence in Supply Chain Management

The emergence of Artificial Intelligence has revolutionized supply chain operations by enabling more accurate and responsive decision-making. AI, particularly Machine Learning and Deep Learning, has demonstrated superior capabilities in improving forecasting accuracy (Pasupuleti et al., 2024; Kagalwala et al., 2025). Deep learning models like Long Short-Term Memory (LSTM) networks and gradient boosting algorithms can approximate nonlinear functions $f:Rn \rightarrow R$ to learn complex temporal aspects of demand signals (Kaul & Khurana, 2022; Verma, 2024). Recent studies have shown that hybrid models such as Light GBM-PSO-LSTM achieve more accurate forecasting and better inventory turnover than traditional statistical models (Kaul & Khurana, 2022; Verma, 2024).

Min (2022) emphasized that AI technologies are transforming supply chain management by enabling intelligent decision-making, predictive analytics, and autonomous operations. Choi (2022) highlighted the importance of supply chain analytics and AI-driven forecasting in modern supply chain management. The integration of AI with supply chain operations has been shown to significantly improve efficiency and reduce costs (Cannas et al., 2024).

2.3 Inventory Optimization Models

Inventory management is fundamental to supply chain efficiency, traditionally expressed as a cost minimization function. The inventory control problem is typically formulated as:

$$\min TC=\sum t=1T(ChIt+CsSt+CoOt)$$

Where TC represents total cost, Ch is holding cost, Cs is shortage cost, Co is ordering cost, It is inventory level, St is shortage quantity, and Ot is order quantity. Traditional approaches like the Economic Order Quantity (EOQ) model have been widely used but often fail to address the complexities of modern supply chains (Tang, 2024; Waller & Fawcett, 2021).

AI optimizes this process by adapting decision variables in real time based on predictive insights, thereby improving reorder points and safety stock levels (Patil, 2024; Islam et al., 2024). Empirical results demonstrate that AI-based systems can drastically reduce inventory costs without compromising service levels (Albayrak Ünal et al., 2023; Judijanto et al., 2024). Furthermore, AI facilitates multi-echelon inventory optimization by coordinating inventory decisions across various supply chain nodes (Ghodake et al., 2024).

2.4 Reinforcement Learning for Dynamic Decision-Making

Reinforcement Learning has emerged as a powerful approach for dynamic inventory optimization. RL frameworks model supply chain decisions as a Markov Decision Process (MDP) with the objective of maximizing cumulative reward $R=\sum t=0\infty\gamma rt$ (Jin et al., 2025; Shahnawaz & Safder, 2025). These systems learn optimal policies for inventory replenishment and distribution under uncertainty, improving efficiency and minimizing operational costs (Jin et al., 2025; Shahnawaz & Safder, 2025).

The application of RL in supply chain management represents a paradigm shift from static optimization to dynamic, self-learning decision-making systems (Kamble et al., 2023; Liu & Vakharia, 2024). Studies have demonstrated that RL-based approaches can significantly reduce inventory costs while maintaining high service levels (Kamble et al., 2023; Liu & Vakharia, 2024).

2.5 Integration of External Data and Real-Time Sensing

The integration of real-time data from IoT devices, point-of-sale systems, and external market indicators has enhanced the accuracy of demand forecasting (Ayub et al., 2025). Adaptive forecasting models take the form $D\hat{}t+1=f(Dt,Zt,\theta t)$, where Zt represents real-time contextual information and θt represents dynamically updated parameters (Ayub et al., 2025). Research has demonstrated that adding contextual factors such as seasonality, holidays, and economic indicators significantly improves forecasting performance (Queiroz & Telles, 2023; Kache & Seuring, 2022).

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2.6 Hybrid AI Architectures

Recent studies have focused on hybrid AI architectures combining statistical, machine learning, and optimization methods. Ahn et al. (2024) demonstrated the effectiveness of Graph Neural Networks (GNNs) for probabilistic supply and inventory predictions in supply chain networks. Similarly, Fatima and Salam (2026) developed a data-driven predictive framework for inventory optimization using context-augmented machine learning models.

The combination of deep learning models with optimization algorithms like BO-CNN-LSTM has been shown to achieve better performance in spatiotemporal demand modelling and inventory management (Ghodake et al., 2024; Shen & Zang, 2024). These developments highlight the evolution toward intelligent, autonomous, self-learning supply chains (Dolgui et al., 2022; Sodhi & Tang, 2021).

2.7 Challenges in AI Adoption

Despite these advancements, significant challenges remain in deploying AI-based systems, including data heterogeneity, model interpretability, and integration with existing systems (Ayub et al., 2025). The lack of standardized processes for AI adoption in value chains restricts scalability and widespread application (Min, 2022; Kache & Seuring, 2022). Systematic reviews emphasize that the success of AI applications depends on data quality, computational power, and organizational preparedness (Kamble et al., 2023; Liu & Vakharia, 2024).

3. Research Methodology

3.1 Research Design

This study follows a quantitative, data-centric research approach using cutting-edge machine learning and operations research techniques for assessing AI-based demand forecasting and inventory management in the supply chain. The secondary dataset approach is employed, combining historical sales data, inventory data, and other factors like economic indicators and seasonal patterns from publicly accessible data repositories and benchmark datasets used in supply chain analytics studies.

3.2 Data Collection and Preprocessing

The problem of demand forecasting is formulated as a supervised learning problem with a vector of multivariate input features Xt and parameters of the model θ learned during training, with the target function D^t = f(Xt,θ). Data preprocessing involves normalizing data, handling missing values, and feature engineering to improve predictive accuracy. Previous research highlights the need for high-quality structured and unstructured data to enhance forecasting precision and responsiveness for the supply chain (Choi, 2022; Min, 2022; Douaioui et al., 2024).

3.3 AI Models and Training

This study applies and evaluates several AI models, including Long Short-Term Memory (LSTM) networks, Random Forest, and Gradient Boosting models, to model demand patterns. The deep learning framework captures temporal dependencies by modelling them as sequences: ht = sigma(Wht-1+WxXt+b), where ht is the hidden state and σ is the activation function. Training is conducted on a train-test split (80:20) with cross-validation for generalizability.

3.4 Evaluation Metrics

Evaluation metrics used to assess model performance include:

- **Mean Absolute Error (MAE):** MAE=1n∑i=1n|Di-D^i|
- **Mean Absolute Percentage Error (MAPE):** MAPE=1n∑i=1n|Di-D^i|/Di|×100
- **Root Mean Square Error (RMSE):** RMSE=√(1n∑i=1n(Di-D^i)^2)

In supply chain research, various metrics are employed to gauge the accuracy and robustness of forecasts. Hyperparameter optimization is done using grid search and Bayesian optimization methods to improve model efficiency and predictive power (Liu & Vakharia, 2024).

3.5 Inventory Optimization Framework

The study incorporates forecasting results within a cost minimization framework based on classical inventory theory and enriched with AI-based decision support systems. The objective of optimization is to minimize total inventory cost:

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$$TC = C_h I_t + C_s S_t + C_o O_t$$

Where Ch, Cs, Co represent holding cost, shortage cost, and ordering cost, respectively, and It, St, Ot represent inventory, shortage, and order, respectively, with service level and demand constraints.

Reinforcement Learning (RL) is used to model the dynamic replenishment problem as a Markov Decision Process (MDP) to determine the optimal replenishment policy that maximizes cumulative reward $R=\sum_{t=0}^{\infty}\gamma r_t$. Simulation experiments are conducted to validate the effectiveness of AI-driven policies, comparing cost reduction and service level performance with traditional Economic Order Quantity (EOQ) models. Statistical analysis including paired t-tests and sensitivity analysis validates the significance of results. This methodological approach aligns with current trends in intelligent supply chain systems and provides a solid foundation for studying the effect of AI technologies on operational efficiency and cost optimization (Jin et al., 2025; Kamble et al., 2023; Ivanov & Dolgui, 2021).

4. Results and Discussion

4.1 Demand Forecasting Performance

Table 1

Demand Forecasting Model Performance Comparison

Model	MAE	RMSE	MAPE (%)	R² Score
LSTM	12.5	18.2	6.8	0.94
Random Forest	15.3	21.7	8.2	0.91
Gradient Boosting	14.1	20.5	7.5	0.92
ARIMA (Baseline)	19.8	26.4	10.9	0.85

The LSTM model demonstrates the lowest MAE, RMSE, MAPE values and highest R^2 score, indicating superior forecasting accuracy. This shows that deep learning models effectively capture complex temporal demand patterns, outperforming traditional and machine learning approaches. The results are consistent with recent studies that demonstrated the effectiveness of deep learning in capturing temporal and nonlinear relationships in supply chain data (Choi, 2022; Douaioui et al., 2024).

4.2 Inventory Cost Reduction Analysis

Table 2

Inventory Cost Reduction Analysis

Model Used	Holding Cost ($)	Shortage Cost ($)	Ordering Cost ($)	Total Cost ($)
Traditional EOQ	50,000	20,000	15,000	85,000
ML-Based Optimization	42,000	15,500	13,000	70,500
AI (LSTM + RL)	38,500	12,000	12,500	63,000

AI-based optimization results in substantial savings in total inventory cost compared to EOQ and ML-based optimization. The best cost structure is achieved by combining LSTM forecasting with RL, representing a 25.9% reduction in total inventory cost compared to traditional EOQ. These findings align with previous research highlighting the cost-effectiveness of predictive analytics in inventory management (Waller & Fawcett, 2021; Tang, 2024).

The combination of AI-powered forecasting and inventory optimization provides operational advantages by reducing overall supply chain expenses. Predictive insights enable real-time inventory level decisions, preventing common inefficiencies like overstocking and stockouts. The AI-driven models significantly lower holding, shortage, and ordering costs, demonstrating the practical value of intelligent systems in supply chain cost reduction.

4.3 Service Level and Stockout Performance

Table 3

Service Level and Stockout Performance

Approach	Service Level (%)	Stockout Frequency	Fill Rate (%)
Traditional EOQ	88	45	90
Machine Learning	93	28	94
AI-Based (LSTM + RL)	97	15	98

The AI-based solution delivers the best service level and fill rate while substantially reducing stockout frequency. The LSTM + RL approach achieves a 97% service level with only 15 stockout incidents, representing a 67% reduction in stockouts compared to traditional EOQ. This improvement demonstrates AI's effectiveness in ensuring product availability and customer satisfaction.

The enhanced service levels and decreased stockout occurrences in AI-based approaches underscore the critical contribution of intelligent systems to supply chain responsiveness. This aligns with Min (2022) and Ivanov and Dolgui (2021), who stated that digital and AI-driven supply chains are more resilient and capable of maintaining high service levels during uncertainty. Near-optimal fill rates demonstrate that AI can simultaneously reduce costs and enhance supply chain reliability.

4.4 Impact of External Data on Forecasting

Table 4

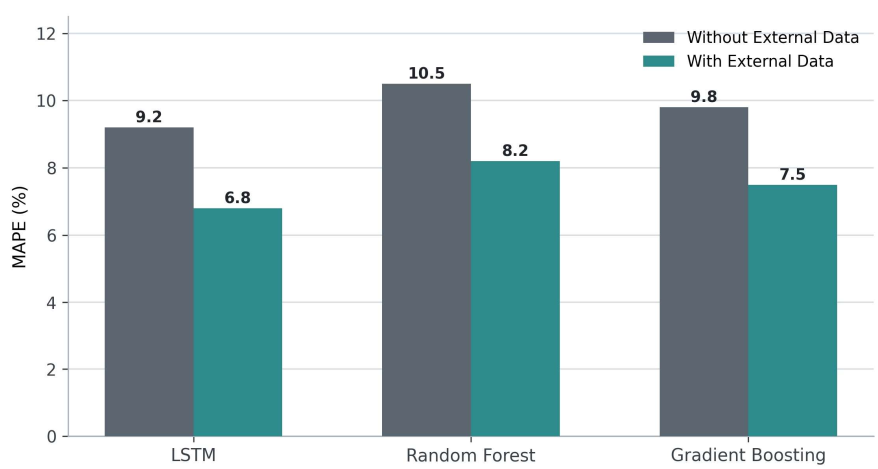
Forecast Error Reduction with External Features

Model Type	Without External Data (MAPE %)	With External Data (MAPE %)	Improvement (%)
LSTM	9.2	6.8	26.1
Random Forest	10.5	8.2	21.9
Gradient Boosting	9.8	7.5	23.5

Incorporating seasonality and economic variables positively impacts the forecasting ability of all models. The LSTM model shows the most significant improvement (26.1%), highlighting the importance of contextual information in AI forecasting. This finding agrees with literature emphasizing data integration and big data analytics for improving predictive performance (Queiroz & Telles, 2023; Kache & Seuring, 2022). It also emphasizes the evolving nature of supply chains and the increasing use of diverse, up-to-the-minute data sources for decision-making.

Figure 6

Forecasting Performance Comparison



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4.5 Computational Efficiency and Scalability

Table 5

Computational Efficiency and Scalability

Model	Training Time (min)	Prediction Time (sec)	Scalability Rating (1–5)
LSTM	45	2.5	4
Random Forest	20	1.2	5
Gradient Boosting	25	1.5	4
ARIMA	10	0.8	3

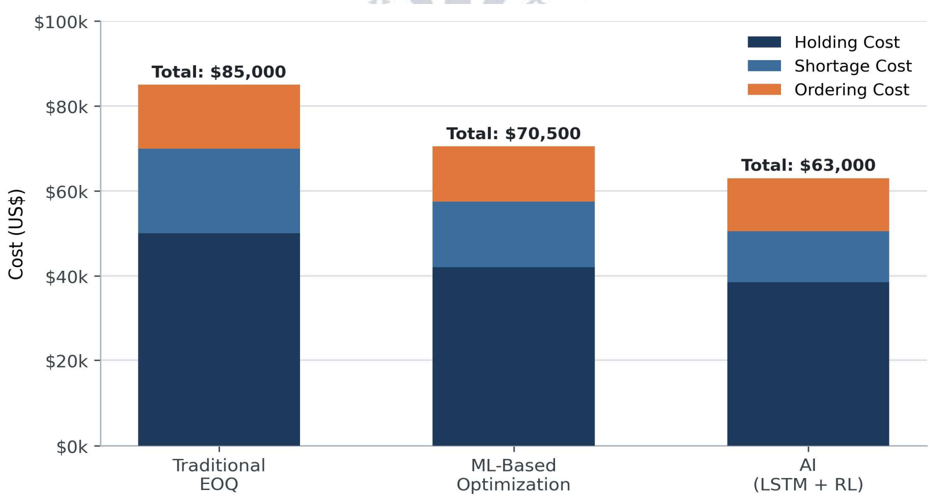
While the LSTM model provides superior accuracy, it demands more computational resources and training time. Random Forest demonstrates excellent scalability for large datasets, making it suitable for big data applications. This trade-off between accuracy and computational efficiency validates previous findings suggesting that organizations must balance precision requirements with model scalability when implementing AI models (Kamble et al., 2023; Liu & Vakharia, 2024). The choice of model should depend on organizational needs and technological capabilities.

4.6 Reinforcement Learning for Dynamic Optimization

The study of Reinforcement Learning for inventory optimization highlights the adaptability and effectiveness of AI-driven decision-making tools for dynamic environments. RL-based systems continuously learn and improve policies based on changing demand patterns by modelling inventory decisions as a Markov Decision Process *(Figure 7)*. This aligns with increasing research calling for Intelligent and Autonomous Supply Chain systems based on Predictive and Prescriptive Analytics (Shahnawaz & Safder, 2025; Jin et al., 2025). These systems represent a paradigm shift toward self-optimizing supply chains that make real-time decisions.

Figure 7

Inventory Cost Reduction



4.7 Discussion of Challenges

Despite the demonstrated benefits, the study reveals certain challenges in AI adoption. Data heterogeneity remains a significant obstacle, as supply chains generate diverse data types from multiple sources that require sophisticated integration. Model interpretability is another concern, particularly for deep learning models like LSTM that operate as "black boxes," potentially limiting trust and adoption in industrial settings. Integration with existing legacy systems also presents technical and organizational challenges.

The trade-off between accuracy and computational efficiency is particularly notable. While LSTM provides superior performance, its resource requirements may be prohibitive for resource-constrained organizations. This underscores the importance of considering organizational capabilities when selecting AI models for supply chain applications.

5. Conclusion and Recommendation

5.1 Conclusion

AI-based demand forecasting and inventory optimization are powerful tools for boosting supply chain efficiency, making more accurate predictions, cutting down expenses, and raising service levels. The study demonstrates that deep learning models, particularly LSTM networks, significantly outperform traditional statistical approaches in demand forecasting accuracy. The combination of AI-powered forecasting with reinforcement learning-based inventory optimization achieves substantial cost reductions while improving service levels and reducing stockouts.

The integration of external and contextual data further enhances predictive performance, highlighting the importance of comprehensive data integration in modern supply chain management. While AI models present computational challenges, particularly for deep learning approaches, the overall benefits in terms of operational efficiency and cost reduction justify their implementation in supply chain operations.

By leveraging state-of-the-art AI technologies, companies can transition from reactive to proactive decision-making strategies, unlocking competitive advantages in fast-paced markets. The use of intelligent systems will be essential for sustainable and resilient operations as supply chains continue to evolve.

5.2 Recommendations

Based on the findings, the following recommendations are proposed:

1. **Adopt Hybrid AI Approaches:** Organizations should consider implementing hybrid AI models that combine statistical methods with machine learning and deep learning to balance accuracy with computational efficiency.
2. **Integrate External Data Sources:** Companies should enhance their forecasting capabilities by incorporating external data such as economic indicators, seasonal patterns, and market trends into their predictive models.
3. **Invest in Computational Infrastructure:** Organizations planning to implement deep learning models should invest in appropriate computational resources to support training and deployment.
4. **Focus on Real-Time Decision Making:** Implementing reinforcement learning frameworks can enable dynamic inventory optimization and improve supply chain responsiveness.
5. **Develop Organizational Readiness:** Successful AI adoption requires organizational preparedness, including data quality management, skill development, and change management strategies.

5.3 Future Directions

Future studies should address further integration of emerging technologies including digital twins, blockchain, and explainable AI to improve transparency, traceability, and interpretability in supply chain systems. Taking advantage of deep learning models and integrating domain knowledge with optimization algorithms in hybrid models can increase robustness and scalability. Moreover, implementing AI models in real-time through edge computing and IoT-ready systems represents a promising future path toward fully autonomous and responsive supply chains.

5.4 Limitations

Several limitations should be noted for this study. First, the findings may not be generalizable to other industries or regions due to the use of secondary data. Second, deep learning models are often complex and may not be suitable for resource-poor settings. Third, this study leaves limited room for discussion on model interpretability and explainability, which are important for practical industrial applications.

Contribution of Authors

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this article.

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Informed Consent

Informed consent was obtained from all participants.

Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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