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Evaluating The Impact Of AI-Based Demand Forecasting Models On Inventory Optimization And Cost Reduction In Supply Chain Management.

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Abstract

Artificial Intelligence (AI) is increasingly integrated into supply chain management (SCM), especially in demand forecasting and inventory control. This study evaluates how AI-based demand forecasting models impact inventory optimization and cost reduction, through a secondary-data analysis of existing empirical and simulation studies. By synthesizing findings from extant literature, we analyse improvements in forecast accuracy, changes in inventory holding costs, reductions in stockouts, and total cost savings. Then, through hypothetical modeling grounded in published simulation parameters, we estimate the magnitude of cost reduction in typical supply chain contexts. Our findings show that AI-based forecasting can improve forecast accuracy (e.g., lowering RMSE/MAE), enabling more optimized inventory policies, which translates into meaningful cost savings (often in the range of **5–45%**, depending on context). However, trade-offs and challenges remain: complex models may incur higher implementation costs, risk overfitting, or fail to always outperform simpler models, depending on demand volatility and data quality. We conclude with managerial implications and suggestions for future research. We conclude with managerial implications and suggestions for future research, in simple terms.

Keywords: Artificial Intelligence (AI), Supply Chain Management (SCM), Demand Forecasting, Inventory Optimization, Cost Reduction, Inventory Control

1. Introduction

In today's dynamic and unpredictable markets, supply chains face substantial challenges in aligning inventory with demand. Overestimating demand leads to excessive inventory holding, while underestimating it causes stockouts and lost sales. Traditional statistical forecasting methods (e.g., moving averages, ARIMA) have limitations in capturing complex demand patterns, especially when data relationships are non-linear or influenced by external covariates. Artificial Intelligence (AI), particularly Machine Learning (ML) and deep learning, offers the potential to enhance demand forecasting by learning from large volumes of historical data, including external variables, and adapting to changes more quickly. These improved forecasts can feed into inventory optimization policies (like order-up-to rules, dynamic lot sizing), reducing costs and improving service levels.

This study aims to evaluate **how AI-based demand forecasting models** influence **inventory optimization** and **cost reduction** in supply chain management, relying on **secondary data** (i.e., published empirical and simulation studies). Ensuring smoother supply operations.

2. Literature Review

2.1 AI in Supply Chain Management

A systematic review by Choi, Lambert, and others (2020) found that AI has multiple applications in SCM: demand forecasting, inventory management, procurement, transportation, and risk management. Complementary to this, Alsolbi, Shavaki, Agarwal, et al. (2023) reviewed *big data optimization and management in SCM*, highlighting that AI techniques combined with big data can significantly improve supply chain performance.

A more recent survey (2025) explores key AI technologies—such as ML, natural language processing (NLP), and generative AI—and their roles in demand forecasting and inventory management. Adding clarity to past studies

2.2 AI-Based Forecasting Models and Inventory Optimization

Machine learning and deep learning models have been critically reviewed for demand forecasting in SCM. According to a review by *Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management* (2024), over 119 papers between 2015–2024 were analysed. The review concludes these AI models significantly improve predictive accuracy, but also discusses challenges like data quality, overfitting, model interpretability, and deployment.

Another empirical/simulation study by Wahedi, Heltoft, Christophersen, Severinsen, Saha, & Nielsen (2023) compared classical forecasting methods with ML approaches for inventory planning in a software-consolidation context. They found that ML approaches outperformed classical ones in many scenarios, which allowed for better inventory decisions.

In terms of cost trade-offs, *Enhancing Supply Chain Management: A Comparative Study of Machine Learning Techniques with Cost–Accuracy and ESG-Based Evaluation* (202X) simulated different forecasting models (RNN, XGBoost) and showed that while XGBoost improved service (fill-rate), it did not always minimize cost compared to simpler methods, due to overstocking or stockout costs. Based on empirical evidence.

2.3 Empirical Evidence on Cost Reduction

Alma Kelly (2024) conducted a desk research study (secondary data) on the impact of AI on SCM, sourcing from published reports and journals. Her findings indicate that AI can significantly reduce costs in forecasting, inventory management, logistics, and risk management.

Similarly, a study by Omoyemi Yekeen, Ewim, and Sam-Bulya (2024) observed that AI optimization and predictive analytics in supply chains can lead to **average cost reductions of 10–15 %**, particularly by optimizing inventory levels, improving forecasting, and improving resilience to disruptions.

Also, Kagalwala, Radhakrishnan, Mohammed, Kothinti & Kulkarni (2025) discuss the role of predictive analytics and AI in improving forecast accuracy, thereby reducing inefficiencies in inventory, lowering holding costs, and reducing stock. As widely acknowledge B

3. Methodology

Since this study is based on **secondary data**, the method involves:

1. Systematic literature search in academic databases (e.g., Scopus, Web of Science, Google Scholar) and open-access publications for peer-reviewed articles, simulation studies, and review papers published between 2015 and 2025 on AI demand forecasting, inventory optimization, and cost reduction in supply chains.
2. Data extraction: From each selected study, key quantitative metrics are recorded—forecast error metrics (RMSE, MAE, MAPE), inventory metrics (holding cost, stockout cost, fill rate), and cost-reduction percentages or absolute cost savings.
3. Synthesis: Group studies by type (simulation vs empirical), model type (e.g., RNN, XGBoost), and domain (manufacturing, retail, etc.), and analyse their reported impacts.
4. Hypothetical modeling: Based on reported parameters (from simulation studies), create a simplified model to simulate potential cost savings under typical inventory policy scenarios, to estimate aggregate cost reduction under AI forecasting. Based on prior research

4. Analysis and Findings

explainable AI methods are used (e.g., multi-channel data fusion network) to not only improve accuracy but also ensure interpretability (though specifics vary by study). (Note: while such explainable models are more recent, they highlight the trend.) **.1 Forecast Accuracy Improvements**

- According to the review of ML and deep learning models (2015–2024), many studies report significant reduction in forecasting error when using AI-based models versus traditional statistical methods.
- For example, in the comparative simulation by Wahedi et al. (2023), ML models achieved lower error metrics, which enabled better inventory decisions.)
- In some more advanced models (hybrid deep learning),

Thus, there is strong evidence that AI models improve forecast accuracy, though the magnitude of improvement depends on data, demand volatility, and the specific algorithm. Supported by evidence

4.2 Impact on Inventory Metrics

- The comparative study of RNN and XGBoost in simulation (from *Enhancing SCM …* study) shows that AI forecasting plus optimized inventory policy yields higher *fill rate* (e.g., XGBoost model had fill rate ~85.4%) compared to naive or static models.
- However, more accurate forecasts alone do not always guarantee lowest total cost: in that same study, although XGBoost improved service levels, its total cost was higher

than naive in some scenarios, due to complexities in matching forecast with inventory parameters.

- The desk research by Alma Kelly (2024) synthesizes multiple studies and concludes that AI helps reduce holding costs and minimize stockout risk, contributing to supply chain optimization broadly. With measurable improvement

4.3 Cost Reduction Estimates

- Omoyemi Yekeen, Ewim, & Sam-Bulya (2024) report that AI-based predictive analytics in SCM can lead to **10–15% cost reduction** on average.
- In simulation-based studies, the trade-offs are more nuanced: for instance, *Enhancing SCM …* (the comparative study) noted up to ~45% cost reduction with RNN-based optimized inventory policies compared to naive EOQ/ROP, under certain assumptions.
- The systematic review by Alsolbi et al. (2023) also underscores that big data + AI can reduce inefficiencies and cost but cautions that implementation cost, data quality, and integration challenges may offset some gains. Reducing operational burdens.

4.4 Synthesis and Hypothetical Modeling

Using parameters drawn from the simulation studies:

- Suppose a company currently uses a naive EOQ (Economic Order Quantity) / ROP (reorder point) policy, with a total annual supply chain cost of **USD 1,000,000**, out of which **holding costs = 30%**, **stockout costs = 10%**, and the rest is ordering and operational costs (per *Enhancing SCM …* baseline assumptions).
- If an AI-based forecasting model (e.g., RNN) plus optimized continuous-review policy is applied, and assuming it gives a 45% cost reduction (as in the simulation), then total cost could drop to **USD 550,000**, saving **USD 450,000 annually**.
- Alternatively, if a more conservative scenario (per desk research) of **10–15% savings** is used, the company could reduce costs to between **USD 850,000 and USD 900,000**, saving **USD 100,000–150,000**.

These hypothetical estimations (grounded in literature) illustrate that the degree of cost reduction depends strongly on (a) how much forecasting error improves, (b) the cost structure (holding vs stockout costs), and (c) the inventory policy adopted. Driving practical saving

4.5 Challenges and Trade-Offs

While benefits are promising, studies also note several challenges:

1. **Implementation Cost**: Setting up AI forecasting systems requires investment in data infrastructure, computational power, and skilled personnel.
2. **Data Quality Issues**: Poor, sparse, or biased data can degrade ML model performance.
3. **Overfitting Risk**: Complex models may overfit on historical data, reducing generalizability.
4. **Explainability**: Many deep learning models are black boxes; lack of explainability may hinder adoption and trust.

5. **Integration**: Integrating AI forecasts with existing inventory control systems (ERP, legacy systems) can be non-trivial.
6. **Service vs Cost Trade-off**: As seen in simulation studies, improving service level (fill rate) sometimes increases total cost unless inventory policies are carefully tuned. Underscoring key limitation

5. Discussions

The secondary-data synthesis indicates that **AI-based demand forecasting** has a clearly positive impact on **inventory optimization** and **cost reduction** in supply chain management. Improvements in forecast accuracy (lower RMSE, MAE) directly support more efficient inventory policies, reducing both holding costs and stockout risks.

However, the actual magnitude of cost reduction varies widely. While simulations show up to ~45% cost reduction in idealized settings, real-world empirical studies often report more modest gains (e.g., 10–15%), likely because implementation costs, organizational resistance, and data issues mitigate the theoretical benefits.

Therefore, managers should:

- Perform a **cost–benefit analysis** before implementing AI forecasting: estimate potential forecast gains, required investment, and expected cost savings.
- Pilot AI forecasting in a limited domain (e.g., one product line) to measure actual impact.
- Focus on **data quality and governance**: clean, rich historical data (including external variables) will significantly influence model performance.
- Align forecasting models with inventory policies: simply improving forecast accuracy is not enough; the inventory control system must be adapted to extract cost savings.
- Address organizational and change-management challenges: training, explainability, and stakeholder trust are key. Clarifying real world impact

6. Conclusion

AI-based demand forecasting offers significant potential to optimize inventory and reduce supply chain costs. Through secondary-data analysis, this study shows that forecast accuracy improves, leading to better inventory decisions, and cost reductions ranging (in literature) from modest (10–15%) to very large (up to ~45%) depending on context. However, realizing these benefits in practice requires careful implementation, good data, and alignment between forecasting and inventory policies. Future research should focus more on real-world empirical studies (not just simulations), cross-industry comparisons, and the long-term ROI of AI in SCM. Indicating broader significance

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