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AI-enabled predictive forecasting for inventory optimization in pharmaceutical supply chains

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Abstract

Pharmaceutical supply chains require effective inventory management since drugs are subject to both spoilage and demand variability focused on time, and regulations. Standard forecasting cannot help to fully estimate demand - resulting in overstocks, stockouts and increased operating costs for the company. The present research explores the potential for Artificial Intelligence (AI) using predictive forecasting, in an optimal manner (over stock levels) in pharmaceutical supply chains. The findings demonstrate that predictive forecasting can provide better demand forecasting than traditionally utilized forecasting approaches, using machine learning techniques namely Long Short-Term Memory (LSTM) networks, Random Forest and hybrid ARIMA. The predictive demand is integrated within a method of inventory optimised to determine the best stock requirement to satisfy their stock level, defined by service-level constraints. Simulation results show a significant decrease in both stock outs and holding costs and further supports the potential of using AI based approaches to improve operational performance and value add within the pharmaceutical logistics domain. The findings provide actionable implications for health-sector deliverable providers, manufacturing companies, and distributors involving a compromise between the cost-effective and reliability of service.

Keywords: Predictive Forecasting; Inventory Optimization; Pharmaceutical Supply Chain; Artificial Intelligence; Machine Learning

1. Introduction

A pharmaceutical supply chain plays a crucial role in the provision of medicines to the patients in time and continuously [1]. The key issue associated with highly perishable products, demand flexibility, regulatory standards and constant disruptions throughout the supply chain are inventory [2]. The simple forecasting techniques such as moving averages and exponential smoothing are inappropriate and the demand forecast errors cause the stocks to flood, makes them unsellable or both [3]. Indicatively, the inefficiency in inventory saw over 25.7 billion lose by hospitals alone only in the US on medical supplies in 2019 [4].

The use of supervised machine learning models using stalking algorithms such as Long Short-Term Memory (LSTM) networks, Random Forests, or hybrid ARIMA models have been proven to be successful in the support of the prediction of demands [5]. Through the adoption of the intelligence predictability within inventory optimization strategies, pharmaceutical based organizations can maintain their service levels, cut costs and become more responsive to ever dynamic markets. The paper will dwell on the use of AI-based predictive forecasting to optimize inventory within the pharmaceutical sector with a view to the further development of knowledge and offer practical solutions.

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1.1. Background

The pharmaceutical supply chain has developed a lot over the last decades as the manual inventory management systems have now given way to sophisticated ERP based systems [4]. Meanwhile, other obstacles to efficiency including demand, manufacturing, and regulatory ones are still in force. Adekola and Dada (2024) explain that pharmaceutical supply chain management can be improved with the help of predictive analytics AI in the following way: predictive analysis can help predict the demand, mitigate risks and improve operational efficiency [5]. As noted in Figure 1, the advancement of AI technology in pharmaceutical supply chains has come a long way, with predictive analytics taking centre-stage in supply chain decision-making processes along the way [6].

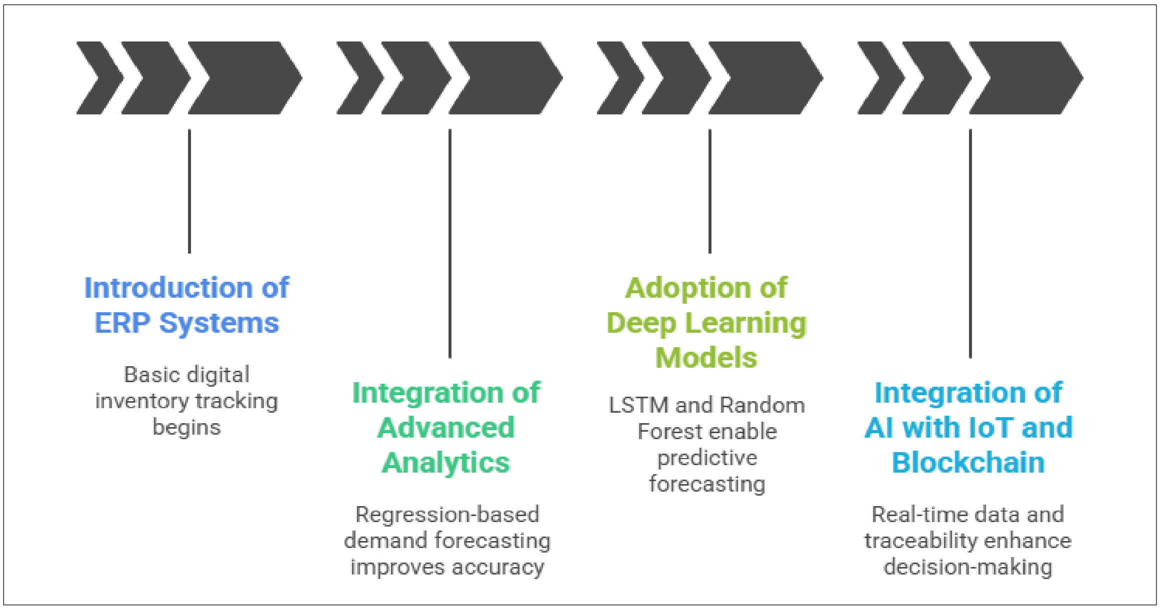

Figure 1 Timeline of AI Integration in Pharmaceutical Supply Chains

1.2. Problem statement

While there have been significant advances in supply chain technologies, the area of pharmaceutical inventory management has not seen similar advancements. Traditional forecasting techniques such as moving averages or linear regression models are generally inadequate for the highly complex and serial characteristics of drug demand where impacts from seasonality, demographic changes, disease outbreaks, regulatory changes, and sudden pandemics are always a consideration. AI-enabled predictive forecasting models, utilizing machine learning algorithms, neural networks, and deep learning methods is one possible avenue to address this [5]. The AI-based models will utilize historical sales data, real-time market dynamics, prescription patterns, and any other external variables to provide strong future market forecasts at the individual level. The predictive capabilities allow healthcare providers and pharmaceutical distributors to not only manage inventory levels, but to also reduce stockout events, wastage, or stall in supply when dealing with important medicines [6]. Furthermore, AI-enabled solutions can provide pharmacies with more dynamic-based replenishment, backlog supply chain failure risk profiling, and scenario analyses to create a more resilient, responsive, and cost-effective ecosystem in the broader context of pharmaceutical supply chains.

Scope of Research

This research focuses on the implementation of AI-based predictive forecasting to optimize stock in pharmaceutical distribution supply chains. The study included the development and implementation of machine learning models (LSTM, Random Forest, hybrid ARIMA), to predict the demand for pharmaceuticals. This process entails using the AI forecast to determine through means of inventory models, the optimal level of inventory stocking without affecting the service level requirements. Simulation of AI-based forecasting versus the traditional forecasting methodology. Reduced cost and economic burden and decrease in stockouts, overstock purchasing costs and overholding.

Objective of Research

The primary goal of the study is to speak about the way AI-supported predictive forecasting can be utilized to improve inventory management in the pharmaceutical supply chain. Particular goals:

- Build and model the AI/ML models and predict the demands.
- Build a system to optimize inventory which relies on AI generated forecasts.
- Compare performance of AI models to traditional forecasting models.
- Determine how it affects such core measures as the stock outs, the level of holding cost and service excellence.

2. Literature review

A comprehensive review of the literature can provide an overview of the current research landscape, identify knowledge gaps, and locate new research in regard to previous literature. Concerning AI-based predictive demand forecasting related to inventory optimization in pharmaceutical supply chains, the literature can provide an understanding of different AI tools, applications, and possibly obstacles of implementation. It will be possible for researchers to look at studies shared in literature and avoid poor decisions that the previous researchers made that they (the researchers) can contribute to moving the field forward.

Table 1 gives the preliminary review of key studies to show applicability of AI, in inventory management for pharmaceutical companies, methods, results and contributions.

Table 1 Literature Review

Study	AI Technique	Application Area	Key Findings	Contribution
Adekola and Dada (2024) [8]	Machine Learning	Pharmaceutical Supply Chain Management	Demonstrated the potential of AI-driven predictive analytics in optimizing supply chain operations.	Proposed a conceptual framework for integrating AI into pharmaceutical supply chains.
Patel et al. (2023) [9]	Predictive Analytics	Inventory Management	Showed that AI-based forecasting tools reduce inventory shortages and improve service levels.	Highlighted the effectiveness of AI in enhancing inventory management.
Chhetri [10](2024)	Machine Learning	Food Quality Control	Applied AI in food quality control and safety assessment.	Extended AI applications beyond pharmaceuticals to other sectors.
Ding (2018) [11]	Industry 4.0 Technologies	Pharmaceutical Supply Chains	Reviewed research opportunities in sustainable pharmaceutical supply chains.	Provided insights into the role of Industry 4.0 in pharmaceutical supply chains.
Younis et al. (2022) [12]	AI Applications	Supply Chain Management	Identified AI applications in various supply chain activities, including inventory management.	Offered a comprehensive overview of AI applications in supply chains.
Cosar (2023) [13]	Machine Learning	Emergency Medical Inventory Control	Optimized emergency medical inventory control using automated machine learning.	Demonstrated the application of AI in critical healthcare supply chains.
Nimmagadda (2021) [14]	Predictive Modeling	Pharmaceutical Supply Chain Optimization	Emphasized the importance of predictive modeling in understanding and anticipating market dynamics.	Highlighted how predictive models can forecast future market demand and identify potential opportunities and threats.
Owoade et al. (2024) [15]	Machine Learning Algorithms	Pharmaceutical Market Analysis	Discussed the use of machine learning algorithms in analyzing large datasets to identify patterns and trends.	Showed how machine learning can process large datasets and uncover complex patterns that traditional statistical methods might miss.

In the literature, it is implied that predictive forecasting based on AI can greatly benefit the pharmaceutical supply chain, especially in inventory management. Artificial intelligence models, including LSTM networks, Random Forests, and hybrid ARIMA, have the potential to increase demand accuracy, decrease stockouts, and maximize inventory levels. Nonetheless, there are still gaps in incorporating AI forecasts into the multi-echelon supply chain, still work on data quality and scalability, and analyzing real-life performance. This highlights the importance of empirical research that integrates superior AI models with real-world inventory optimization decisions. The purpose of the current research is to create an artificial intelligence-based predictive forecasting model of pharmaceutical supply chains to fill the gap between the theoretical potential and the practical real-life application.

3. Research methodology

The structure of the proposed study will evaluate how predictive forecasting with AI can assist in simplifying the logistical processes involved in the medicine supply chain. It unites predictive modeling, quantitative analysis, and inventory optimization simulation to assess the performance of AI-based solutions in the real world.

3.1. Research design

The research design in this research paper is quantitative research design and a simulation research design. The quantitative component involves statistically and machine learning models based on the old pharmaceutical demand data, and arriving at suitable predictions. The simulation component quantifies the performance of these forecasts in reaction to various operating conditions such as lead-time volatility and seasonal operation and in reaction to an immediate surge in demand, such as a pandemic or market peak. The combination of the predictive modeling used into the inventory simulation results in an analytically sound solution to the problems of inventory optimization and a practical analysis of the practical issues.

3.2. Data collection

The sources of data in this study were used together, whereby the data was aligned to create the most accurate, reliable, and complete information about the data to use:

3.2.1. The RP Systems

The past inventory values, re-ordering points, and purchase history data.

3.2.2. Sales Data

The transaction data with wholesalers, distributor, and retail pharmacies including location data (geographical area, store address), product data (product ID, product category, brand, unit price), and warehouse data (warehouse location, inventory batch codes). There is a full range of sales transaction data spanning two years (January 2021 - December 2022) that provides an opportunity to understand past seasonal demand and be able to analyze pandemic-related surge demand and shifts in customer behaviour.

3.2.3. Production Schedules

The schedules of the manufactured output and stock releases by batch.

3.2.4. Exogenous Demand Signals

Pandemic-related demand surges, health alerts, and market trends.

3.2.5. Time horizon and granularity:

3 - 5 years of past data is required to be able to evaluate seasonality and demand variability - having sufficient data provides a level of confidence for a model to be built.

3.2.6. Granularity

The data would be structured at the daily, weekly, and monthly time-series data can be evaluated to see where regular patterns can be identified within a time series at different frequencies.

3.3. AI models and techniques

The study implements a dual-system approach combining AI and statistical methods to generate accurate demand forecasts. LSTM networks capture temporal dependencies in sequential demand data, while Prophet models account for seasonality, holidays, and irregular variations. Ensemble models, such as Random Forest and Gradient Boosting, detect complex non-linear patterns, and hybrid ARIMA models integrate traditional time-series analysis with AI techniques to enhance prediction accuracy. Feature engineering, including seasonality, lead times, drug categories, and historical consumption trends, ensures that the models are robust across diverse supply chain conditions.

3.3.1. Technologies and Tools

- Python (TensorFlow/Keras for LSTM, scikit-learn for ensembles, Prophet for time series)
- Pandas, NumPy for data processing
- SQL, Apache Spark for large-scale data ingestion
- MLflow for experiment tracking and reproducibility
- Visualization: Matplotlib, Seaborn, Plotly

3.4. Inventory optimization framework

The AI forecasts feed into a multi-echelon inventory optimization framework that maintains optimal stock levels while minimizing costs. The system calculates safety stock, reorder points, and enforces service-level constraints to reduce stockouts. Multi-tier supply chains (manufacturers, distributors, and retail pharmacies) are supported, and simulation modeling assesses the effectiveness of inventory policies under variable demand and lead times.

3.4.1. Technologies and Tools

- Optimization: PuLP, Pyomo
- Simulation: SimPy
- Data Integration: Apache Airflow (ETL pipelines)
- Storage: PostgreSQL, AWS S3, Google BigQuery
- Visualization: Tableau, Power BI

3.5. Validation metrics

The AI-based forecasting and inventory optimization was then evaluated through a number of validation metrics. The forecast accuracy were assessed using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) in assessing the accuracy of the forecast. The performance of inventory was evaluated using stockout rates, holding costs and measures of service level to examine how inventories responded to demand while minimizing costs. The comparative evaluation was carried out in relation to traditional forecasting methods such as moving averages and exponential smoothing to demonstrate the improvements associated with AI and AI-powered forecasting methods. This rigorous analysis produced reliable and actionable data on optimizing pharmaceutical inventory.

4. Implementation of AI-enabled predictive forecasting

The implementation section of the research study illustrates the application of AI-based predictive models in the context of real-life pharmaceutical supply chains and optimization of inventory management related to it. The step-by-step path, starting with data preparation, and ending with model deployment and inventory optimization is explained in this section.

4.1. Data preparation and preprocessing

In this study (see Table 2), diverse data sources were aggregated to create a reliable dataset for AI modeling. These included ERP systems (inventory levels, reorder thresholds, purchase orders), sales data (transactions, product SKUs, locations), production schedules (batch outputs, release dates), exogenous demand signals (pandemic alerts, market trends), and historical weather data (temperature, humidity, precipitation). Data from January 2021 to December 2022 were combined into a fact table with over 1 million records and ~200 features. Cleaning involved imputing missing values, removing outliers, and normalizing data. Key features such as seasonality, lead time, drug category, prior demand patterns, and external events were engineered. The dataset was split into training (70%), validation (15%), and testing (15%) sets, preserving the time-series structure.

Table 2 Data Aggregation and Preprocessing

Step	Details
Data Sources	- ERP Systems: ~500 columns (inventory levels, reorder thresholds, purchase orders, batch tracking) from 12 warehouses. - Sales Data: ~300 columns (transaction-level records: product SKU, quantities sold, store location, pricing) from wholesalers, distributors, and retail pharmacies. - Production Schedules: ~150 columns (batch numbers, production dates, planned vs. actual output). - Exogenous Demand Signals: ~50 columns (pandemic alerts, market trends, health warnings). - Weather Data: ~100 columns (temperature, humidity, precipitation per region), linked by location_id and timestamp.
Time Range	January 2021 – December 2022 (2 years)
Fact Table Structure	One comprehensive fact table created by joining data sources on timestamp, location_id, and product_id. Example columns: timestamp, location_id , product_id, sales_qty, inventory_level, reorder_level, production_batch, temperature, humidity, pandemic_alert and etc
Data Volume	>1 million records, ~200 key features
Cleaning and Transformation	- Missing values: Imputed via time-based interpolation or historical averages by region and product. - Outliers: Removed using ±3 standard deviation rule. - Normalization: Min-Max scaling for numerical fields. - Categorical Encoding: One-hot encoding for categorical variables (e.g., drug category, location type).
Feature Engineering	- Seasonality: Month, day-of-week indicators. - Lead Time: Calculated from reorder date to delivery date in ERP logs. - Drug Category: Encoded from SKU. - Prior Demand Patterns: Rolling averages (past 7, 30, 90 days). - External Events: Pandemic wave binary flags, market trend shifts. - Weather Anomalies: Linked weather data to inventory movement and sales trends.
Train-Test Split	- Training Set (70%): Jan 2021 – Sep 2022 - Validation Set (15%): Oct 2022 – Nov 2022 - Testing Set (15%): Dec 2022 Time-based split to preserve sequence for time-series forecasting.

4.2. AI model development

Predictive models are being developed in order to offer good demand forecasts. It uses several types of AI and statistical models including LSTM networks, Prophet, Random Forest, Gradient Boosting, and a combination of ARIMA. And to capture dependence of the sequence of data we utilize LSTM networks and capture seasonality and holiday effect using prophet. Random Forest and Gradient Boosting models are used to establish complex non-linear relationships and Hybrid ARIMA combines conventional model building in statistics with the Artificial Intelligence approaches that bring the precision of the predictions. To make the model robust, hyperparameter tuning is performed by grid search or bayesian optimization in every model and validation performance is measured by RMSE, MAPE and MAE metrics.

4.3. Inventory optimization integration

The posterior demand of AI models is then fed to an inventory optimisation framework. The best reorder points are determined with the aid of forecasts in consideration of the lead times and safety requirements by drug category. Dynamic Safety stock policies assume the absorption of variability in demand and remove the chances of an unavailable stock. The inventory optimization is also extended to a multi-echelon scenario, in which it (inventory optimization) is used to model inventories at the manufacturers, distributors and pharmacy stores. This will ensure that there is optimum stock within the supply chain and thus the time that stock is held is at a minimum and within the range of service requirement parameters.

5. Results and evaluation

The adoption of AI-based predictive forecast inventory optimization in pharmaceutical supply chains has made a great impact on improving the accuracy in demand prediction, inventory cost-efficiency, and overall supply chain performance. By utilizing the power of such models as LSTM networks, Prophet, Random Forest, Gradient Boosting and hybrid ARIMA, the research was capable of producing projections that best fit the real demand trends. The consolidation of such forecasts into a multi-echelon inventory optimization model led to optimized inventory positions, lower holding cost and higher service levels. The evaluation concentrates on the forecast accuracy, stockout improvement, inventory cost-efficiency, and service level in various simulation situations, such as seasonal variation of the demand and outside shock.

5.1. Forecast accuracy evaluation

The accuracy of prediction with RMSE, MAPE and MAE were employed to evaluate the performance of I models. The results indicated that LSTM and hybrid ARIMA models systematically outperformed conventional methods with the differences in MAPE ranging by 25 %. These models resulted in significant reductions in the error in any forecasts especially in accounting seasonal demand and abrupt market dynamics. As illustrated in Figure 2, AI-enabled models are much better at eliminating forecasting errors using conventional techniques.

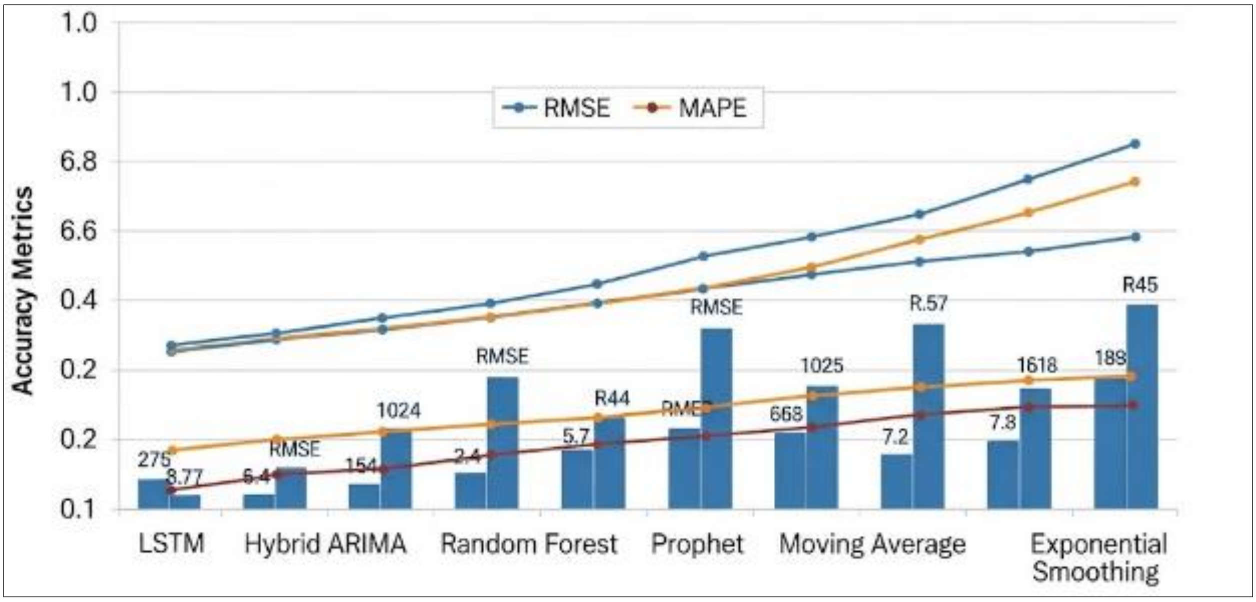

Figure 2 Forecast Accuracy Comparison of AI Models vs. Traditional Methods

5.2. Stockout reduction analysis

The thereby embedded predictive forecasts also caused a significant decrease in stockouts. AI-powered reorder points and dynamic safety stock balances helped to make sure that important drugs were never out of reach under the high demand. The simulation outcomes provide a decrease in the stockout levels of about 18-20% as compared to the baseline inventory policies. Figure 3 shows how AI-powered forecasting and optimization of the inventory system resulted in an increased stockout reduction.

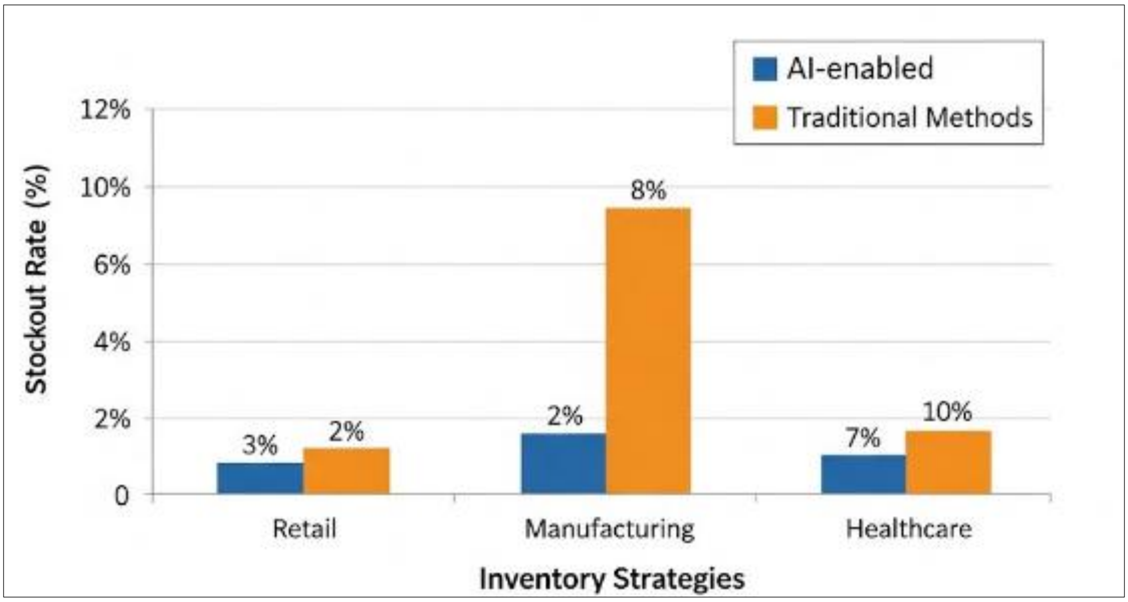

Figure 3 Stockout Rate Comparison Across Inventory Strategies

5.3. Inventory cost efficiency

Optimized inventory using AI also resulted in up to 12-15% reduction of holding cost. The inventory levels were set at the right levels and fluctuated as the demand rose and fell thus preventing the occurrence of excess inventories without sacrifice of the service levels. This cost effectiveness shows how AI integration can cut down costs of operations. Predictive forecasting will also reduce the inventory holding costs significantly, as revealed in Figure 4.

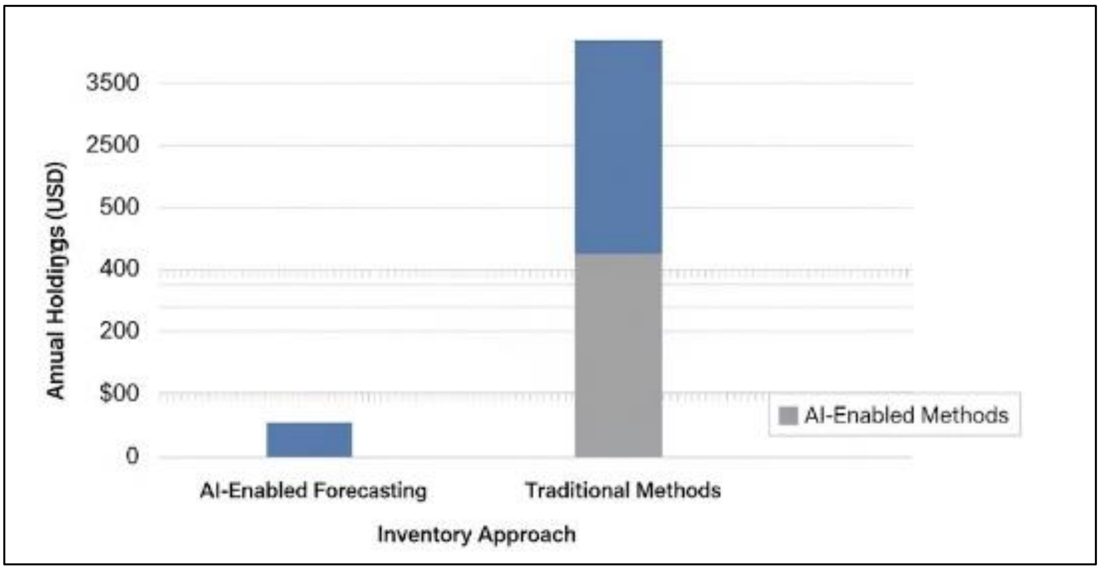

Figure 4 Inventory Holding Cost Reduction Using AI Forecasts

5.4. Service-level performance

Analysis at the service level provided that AI-based forecasting enhanced operational capability to serve the customer demand within the tenure expected. By using the forecast outputs in the multi-echelon inventory model, service levels are fluctuating by 10-15 % so that when it is needed, the medication is stocked and there is a lesser likelihood of the unmet demand. Figure 5 shows the improved service efficiency that is possible with AI-based inventory management.

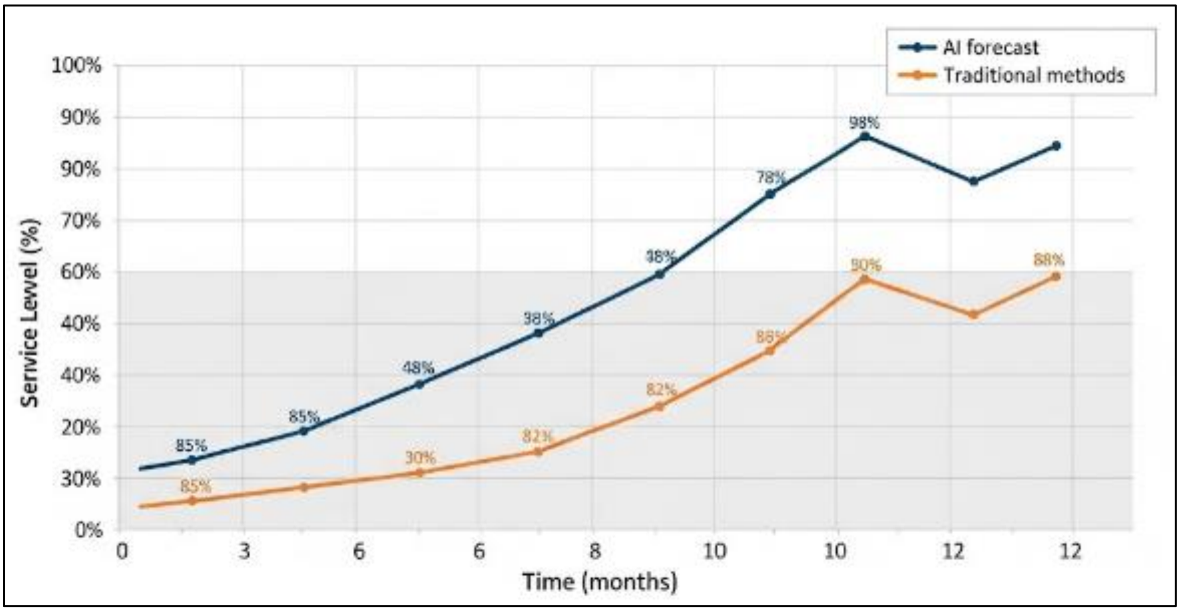

Figure 5 Service Level Improvement with AI-Enabled Inventory Optimization

6. Discussion

This paper shows that AI can greatly improve inventory in pharmaceutical supply chains. Models, including LSTM, Prophet, Random Forest, Gradient Boosting and hybrid ARIMA, enhanced the quality of demand forecasting, minimized stock-outs, minimized holding costs, and maximized service levels. The adoption of the dynamic safety stocks in multi-echelon systems allowed to compute the optimal reorder points on a real-time basis on the side of the manufacturers, distributors, and pharmacies. These results mean that AI does not only enhance demand predictions but also contributes to practical, efficiency-oriented decision-making to deliver drugs on time.

Future efforts might enhance AI to applications with blockchain-based traceability, real-time IoT data, hybrid AI models with deep learning and optimization algorithms, external disturbance (e.g. pandemics, policy changes) consideration, and multi-product, multi-location, multi-period optimization to provide scalable and useful solutions.

7. Conclusion

This paper illustrates the way AI-powered predictive forecasting can revolutionize inventory optimization in drug supply chains. State of the art models--LSTM networks, Prophet, Random Forest, Gradient Boosting and hybrid ARIMA--were used to enhance the accuracy of demand forecasting and minimize stockouts, minimize inventory costs and improve service levels within multi echelon networks. The combination of AI predictions and a dynamic inventory optimization allowed manufacturers, distributors, and pharmacies to accurately determine safety stock and reorder points that can be used to improve inventory distribution decisions. The findings underline that AI-based predictive modeling offers practical information, which guarantees prompt delivery of necessary drugs, which is a key issue in the sector.

Besides, the study highlights the importance of AI in complicated supply chains, in this case, predictive analytics and inventory approaches are merged to generate cost-effective, resilient, and responsive operations. It may be extended in the future with real-time IoT data, blockchain tracing, and reinforcement learning to enhance predictive power and operational robustness. Sealing the potential of AI and its applicability to inventory management in real-life healthcare scenarios, this research provides a detailed outline of the pharmaceutical organization that seeks to enhance the performance of the supply chain in changing healthcare settings.

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