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Integrating Demand Forecasting and EOQ for Inventory Management in the Pharmaceutical Sector

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Abstract

Effective inventory management is critical in the pharmaceutical sector, where the availability of essential medications directly impacts patient care. This study investigates the integration of demand forecasting techniques and inventory optimization to improve supply chain efficiency, focusing on GLYMIN, a vital drug for managing type 2 diabetes. Two forecasting methods, Exponential Smoothing and Linear Regression, were evaluated using sales data. The Linear regression has fewer errors with 771.04 MAD, 766,666.29 MSE, and 4.32% MAPE. The study incorporates Linear Regression forecasts into an Economic Order Quantity (EOQ) model to determine optimal inventory parameters, such as safety stock, reorder levels, and average inventory. Sensitivity analysis and Monte Carlo simulations were conducted to assess the impact of lead time and demand variability on inventory costs and stockout probabilities. Pharmaceutical companies can achieve more effective, responsive, and sustainable inventory management systems by addressing the particular difficulties faced by the industry, such as perishability, regulatory complexity, and demand variability. The proposed framework offers a scalable approach for other medications and contexts. However, the study is constrained by the size and scope of the dataset, suggesting future work could benefit from larger datasets and hybrid forecasting models to capture seasonality and nonlinear trends.

Keywords
Pharmaceutical inventory management, demand forecasting, linear regression, exponential smoothing, and economic order quantity (EOQ).

1. Introduction
Inventory management is strategically planning and controlling an organization's stock levels. Effective inventory management helps to reduce overall system costs, satisfy customer demands, and improve supply chain efficiency by ensuring that the right amount of stock is available at the right time and place(Nallusamy 2021). Effective inventory control is crucial in the pharmaceutical sector to guarantee the supply of vital drugs while reducing expenses and waste. Achieving these goals depends heavily on accurate demand forecasting, which lowers the risk of stockouts or overstocking and allows supply chains to adapt to changing demand. Forecasting techniques like Linear Regression (LR) and Exponential Smoothing (ES) are popular because they are easy to use and can accurately represent demand patterns (Billah et al., 2005). Integrating demand forecasting with inventory management has significantly improved supply chain performance. Research highlights that combining forecasting models with inventory optimization

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strategies, such as the Economic Order Quantity (EOQ) model, reduces costs and enhances service levels (Goltsos et al. 2022). This study highlighted the importance of demand forecasting and inventory management in the pharmaceutical industry by concentrating on GLYMIN, a drug often recommended for type 2 diabetes. Our research aims to improve pharmaceutical supply chain inventory control procedures and forecasting techniques by examining important factors like lead time, demand variability, and production schedules.

1.1 Objective

The primary goal of this study is to create a framework for inventory management and forecasting in the pharmaceutical sector. The study aims to evaluate and compare the accuracy of Exponential Smoothing and Linear Regression for forecasting the demand for GLYMIN using historical sales data, utilize the most precise forecasting technique in an inventory model to ascertain the best operating parameters, including Safety Stock, Reorder Levels, and Economic Order Quantity (EOQ), perform sensitivity analysis to determine how essential factors, like lead time and demand fluctuation, affect safety stock, reorder level and inventory costs, perform monte carlo simulation to analyzes variability in inventory metrics, reflecting uncertainty in demand or lead times to aid inventory optimization.

2. Literature Review

Effective inventory management in the pharmaceutical industry relies heavily on accurate demand forecasting to maintain optimal stock levels, minimize waste, and ensure the timely availability of critical medications. Exponential Smoothing is a preferred method for demand forecasting due to its simplicity and adaptability. Its usefulness in pharmaceutical demand scenarios is demonstrated by Billah, which shows that optimized smoothing constants result in lower error margins (Billah et al. 2005). Additional research highlights the usefulness of ES for short-term forecasting in inventory planning (Kot S et al. 2011).

Linear Regression provides a statistical basis for understanding demand trends. Linear regression successfully incorporates past data to forecast demand in the future (Fildes & Beard 1992). Furthermore, incorporating LR into broader supply chain models enhanced forecasting accuracy by 10% (Ali et al. 2012). Recent research shows ES and LR should be combined with sophisticated methods like neural networks and Monte Carlo simulations. A hybrid model that combined LR and optimization techniques was shown to outperform standalone models by bringing MAPE down to less than 12%(Maitra et al. 2023).Time-series techniques, such as Holt-Winters methods, are crucial for forecasting seasonally adjusted pharmaceutical demand. In situations where demand fluctuated periodically, these techniques performed better than traditional ES (Hua, n.d. 2014).Better model performance was correlated with lower MAD and MAPE scores. Exponential Smoothing consistently achieved MAD reductions of 5-7% over moving averages (Barrow & Kourentzes, 2016). MSE is effective at penalizing large forecast deviations, which is important for high-stakes pharmaceutical inventories (Zhou et al. 2023).MFE identifies systemic biases in forecasts, but it is used less commonly (Ravinder 2013).

The Purchase models, such as the Economic Order Quantity (EOQ) model, concentrate on replenishment tactics. EOQ minimizes the total costs of ordering and holding inventory, making it ideal for high-demand medications. Periodic review models are popular for batch ordering to streamline operations (Alnahhal et al. 2024).Shortage models are used when demand outpaces supply. Backordering and lost sales models are widely used, depending on the criticality of the medication. The models incorporate stockout penalties for essential drugs in order to guarantee high availability (Kumar Yadav et al. n.d.2016).

One study emphasized the importance of demand forecasting in inventory management, focusing on how misalignment and miscommunication between supply and demand across supply chain links result in high inventory costs (Kot S et al. 2011). The best approach to greatly increase forecasting accuracy and inventory management performance is integrating forecasting with inventory management (Goltsos et al. 2022). Forecast-integrated inventory systems optimize pharmaceutical supply chains by balancing service levels with cost efficiency. Simulation-based studies have shown that integrating advanced demand forecasting models, like machine learning, with classical inventory systems reduces waste and ensures the timely availability of critical medications (Douaioui et al. 2024).Demand Forecasting: A Case Study in the Food Industry highlights the importance of accurate forecasts in improving supply chain efficiency and reducing waste, which is equally applicable to the pharmaceutical industry (Silva et al. 2019).

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On Replenishing Items with Seasonal Intermittent Demand emphasizes the need for further development of forecasting and replenishment models to address the challenges of non-stationary intermittent demand, a common characteristic in the pharmaceutical industry (Mitchell & Niederhausen, 2010). The gap between forecasting and inventory management practices has been explored, with recommendations for integrated models that adjust inventory levels dynamically based on real-time demand data (Goltsos et al. 2022). Neural Networks (GNN) were used to present a probabilistic inventory prediction model, which improved inventory accuracy by 20% over conventional techniques (Ahn et al., n.d.).Pharmaceutical companies can improve supply chain efficiency and ensure medication availability by combining dynamic inventory control techniques with demand forecasting methods. An attempt was made to forecast and incorporate a demand dataset with an inventory management model for GLYMIN, a medication essential for controlling diabetes.

3. Methods

Two forecasting methods, exponential smoothing and linear regression, were employed to predict future sales of GLYMIN. The method used in this research is illustrated using a systematic framework. Figure 1 shows a framework with a detailed view of the proposed model. Dotted rectangles indicate each principal step. Rectangles with rounded ends indicate the sub-steps under the principal steps. The diamond shapes indicate the decision to be made.

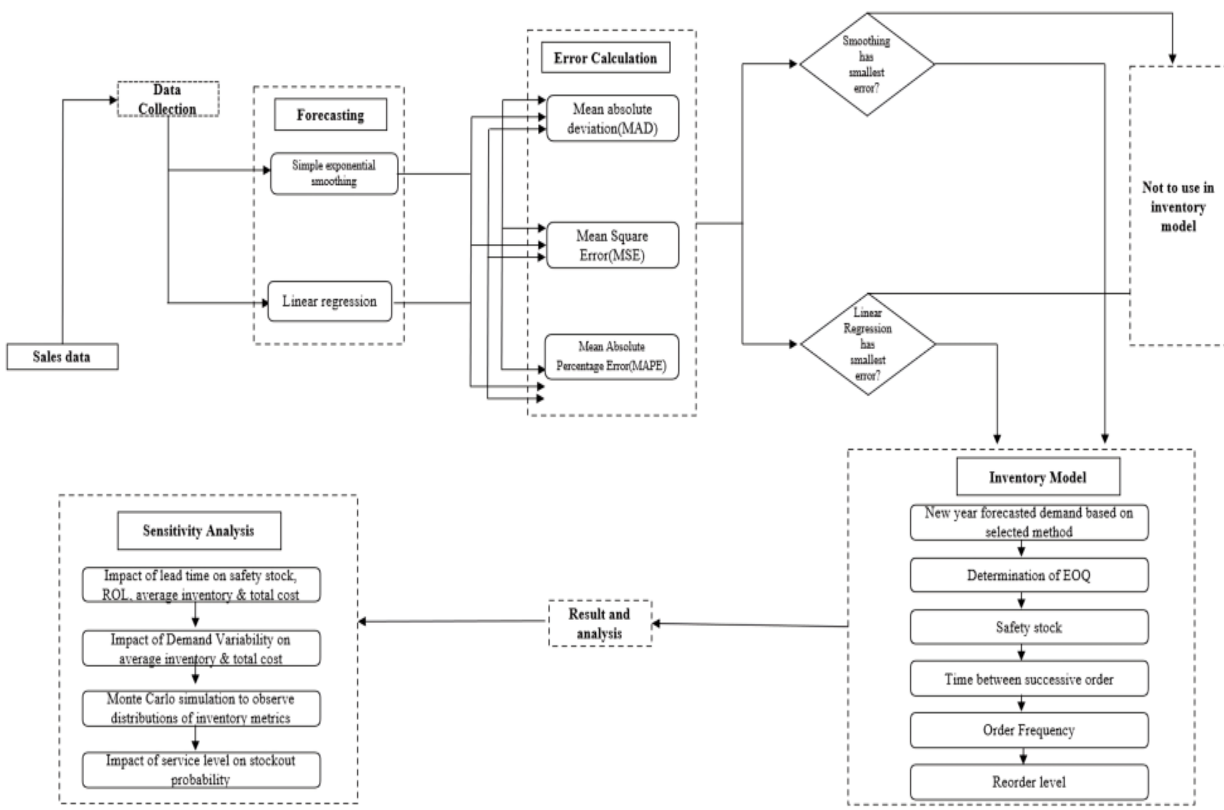

Figure 1. Systematic Framework of Proposed Forecasting Evaluation and Integration with Inventory Mode

3.1 Simple Exponential Smoothing

Exponential smoothing maintains a running demand average and modifies it for every period according to the variation between the most recent average value and the most recent actual demand figure. A crucial part of exponential smoothing is the initial demand estimate for the first period, which forms the basis of all subsequent forecasts.

$$F_t = F_{t-1} + \alpha(D_{t-1} + F_{t-1}) \quad (1)$$

In the eq. (1), D_t is previous period demand, F_t is Forecast and α is Smoothing constant.

3.2 Linear Regression

Linear regression is a statistical method that models the relationship between a dependent variable (sales) and one or more independent variables (time, in this case). A machine learning algorithm was used to perform linear regression and predict the demand for 2023.

$$Y = a + bX \quad (2)$$

In the eq. (3), Y = Dependent variable, X = Independent variable, a = Intercept, and b = Slope (trend).

3.3 Error Metrics

Determining which forecasting technique is the most accurate is significantly impacted by the choice of error measure. Eqs (4)–(6) represent the mean absolute deviation (MAD), mean square error (MSE), mean forecast error (MFE), and mean absolute percentage error (MAPE) used in this study.

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |e_i| \quad (4)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \quad (5)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|e_i|}{y_i} \cdot 100\% \quad (6)$$

3.4 Inventory Model

We use the purchase model with instantaneous replenishment to guarantee a steady and timely supply of Glymin. It meets urgent healthcare demands by cutting lead times and minimizing stockouts.

$$\text{Total Cost} = \frac{D}{EOQ}Co + \frac{EOQ}{2}Cc + \text{D} \times \text{P} \quad (7)$$

In the eq. (7), $\text{D} = \text{anual demand}, \text{EOQ} = \text{Economic Order Quantity}, \text{Co} = \text{Ordering cost}, \text{Cc} =$ $\text{Carrying cost and P} = \text{Purchase cost}$

3.5 Sensitivity Analysis

Sensitivity analysis is performed by varying lead time and demand variability on safety stock, reorder level, average inventory, and total inventory cost to observe the effect of changes. Monte Carlo simulation on inventory metrics and the relationship between service levels and stockout probabilities is also shown here.

4. Data Collection

Square Pharmaceuticals sales data covering a variety of drugs over a 24-month period from January 2021 to January 2022 was gathered. This large dataset comprises monthly sales data for several pharmaceutical items specifically focusing on GLYMIN. Following a comprehensive review of the dataset, GLYMIN was chosen for further investigation because of its significant role in the diabetes care market and the growing prevalence of diabetes in Bangladesh.

5. Result and Analysis

5.1 Numerical Results

Table 1 shows the forecasting values of two methods: simple exponential smoothing and linear regression. Then, different error metrics are calculated for both methods. Error metrics, MAD, MSE, and MAPE, were found to be 904.25, 1,173,432.33, 5.03% for exponential smoothing, and 771.04, 766,666.29, and 4.32% for linear regression. Linear regression provides lower error metrics than exponential smoothing, so we have chosen linear regression for further calculations.

Table 1. Actual value, forecasting value using exponential Smoothing and linear regression

Year	Month	Sales	Exponential Smoothing	Linear Regression
2021	January	17109	18040	16791
2021	February	15880	17854	16900
2021	March	17669	17459	17009
2021	April	15754	17501	17117
2021	May	18053	17152	17226
2021	June	18118	17332	17335
2021	July	17608	17489	17443
2021	August	17518	17513	17552
2021	September	18159	17514	17661
2021	October	19368	17643	17769
2021	November	18353	17988	17878
2021	December	16414	18061	17987
2022	January	17459	17732	18095
2022	February	16976	17677	18204
2022	March	19099	17537	18313
2022	April	17222	17849	18421
2022	May	18082	17724	18530
2022	June	19081	17796	18638
2022	July	18135	18053	18747
2022	August	18684	18069	18856
2022	September	19841	18192	18964
2022	October	19953	18522	19073
2022	November	20124	18808	19182
2022	December	18323	19071	19290

5.2 Graphical Results

Figure 2 shows the actual sales and forecasting sales using exponential smoothing. Based on those historical data, it also shows the predicted January 2023 sales (red star) value. Figure 3 shows a similar graph for linear regression. While exponential smoothing closely resembles recent data patterns, linear regression shows a consistent upward trend.

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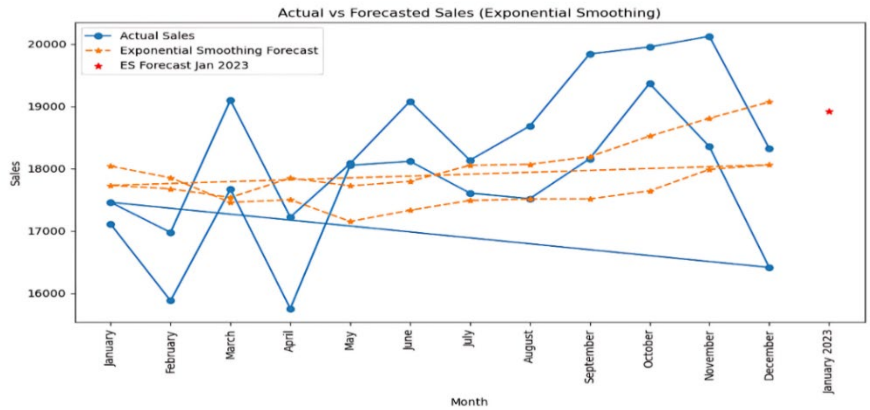

Figure 2. Actual vs forecasted sales(exponential smoothing)

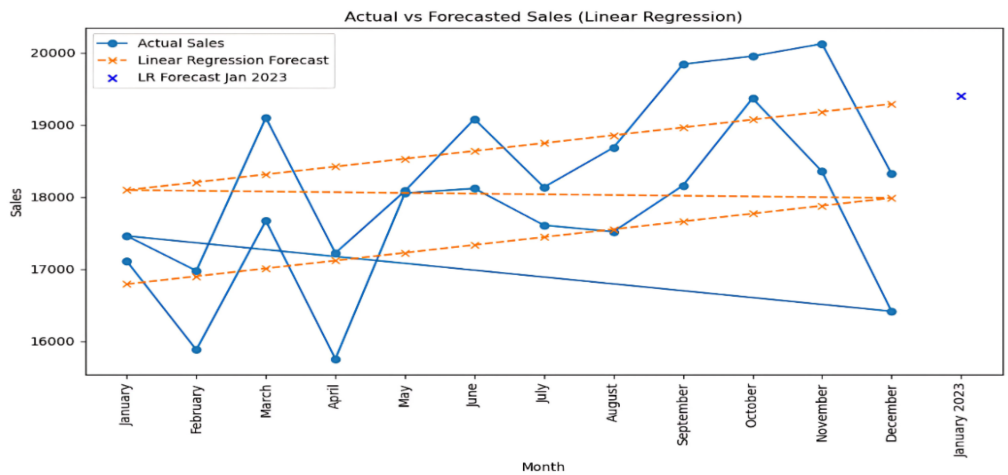

Figure 3. Actual vs forecasted sales(linear regression)

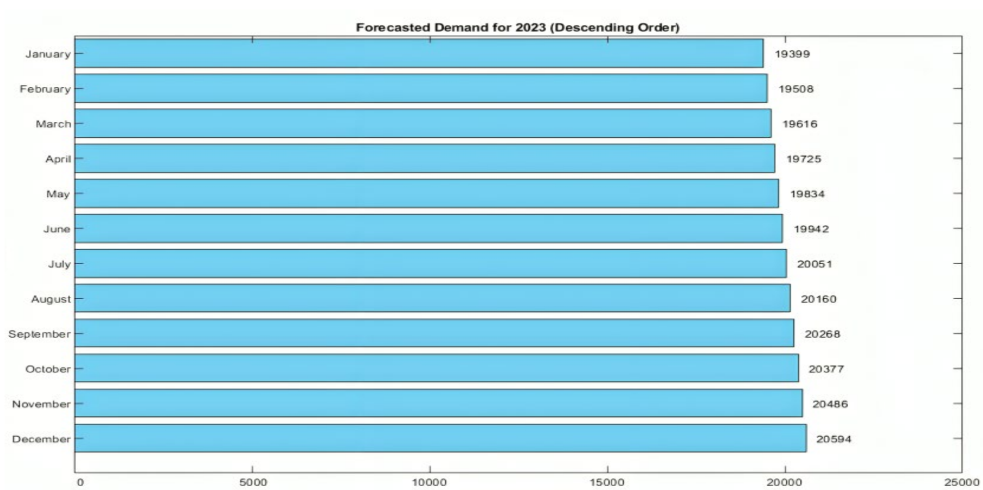

Figure 4. Bar chart of forecasted demand for 2023

As the linear regression method provides lower error metrics than exponential smoothing, it was used to predict demand for 2023. The result is shown in Figure 4. The annual demand for 2023 was calculated to be 239,960 units.

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By integrating this into the inventory model, the following results were obtained: EOQ was 10,954 units, Safety Stock was 406 units, Reorder Level was 9,604 units, the number of orders per year was 22, the time between orders was 16.67 days, the average inventory was 5,477 units, and the total inventory cost was 1,179,380 Taka. The inventory model is shown in Figure 6.

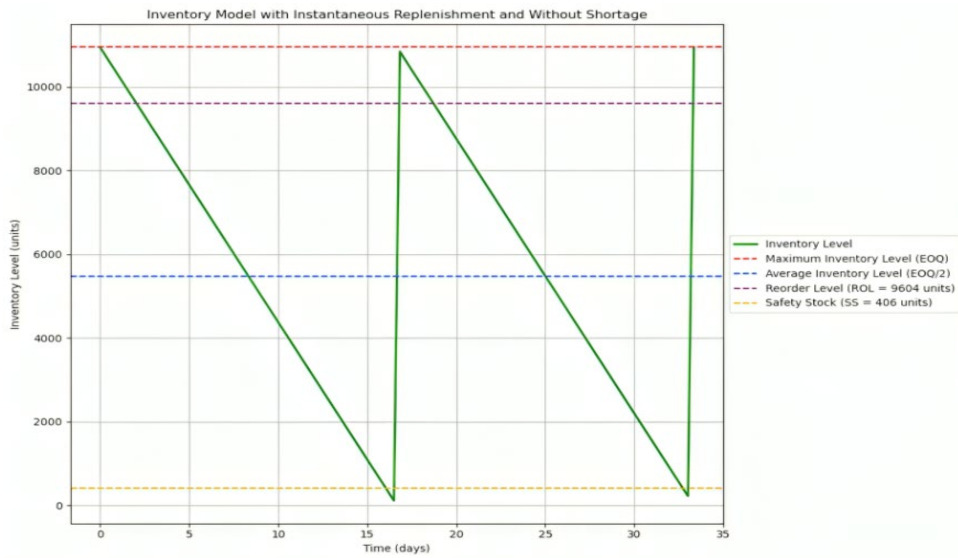

Figure 5. Inventory model

5.3 Sensitivity Analysis

Sensitivity analysis examines the effects of varying independent variable values on a given dependent variable under particular assumptions.

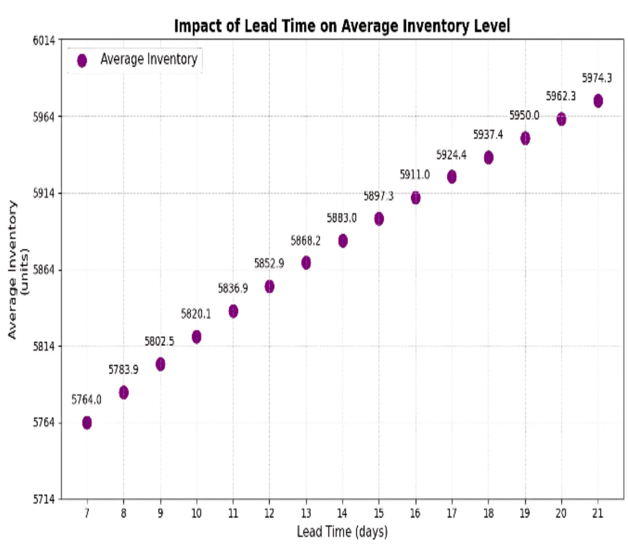

Figure 6. Average inventory vs lead time

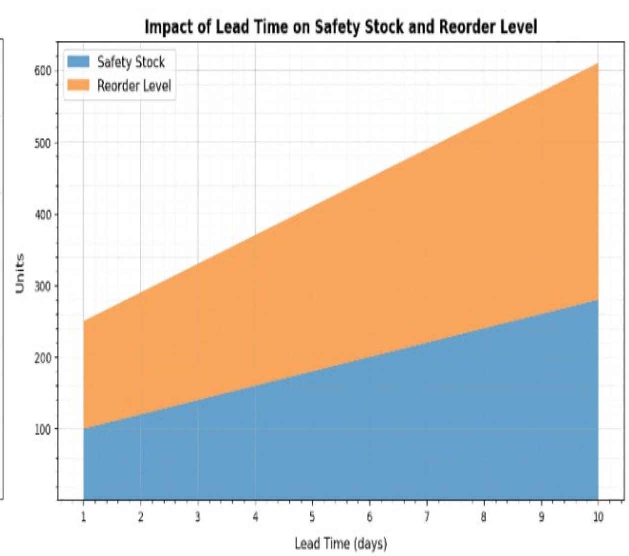

Figure 7. Safety stock, reorder vs lead time

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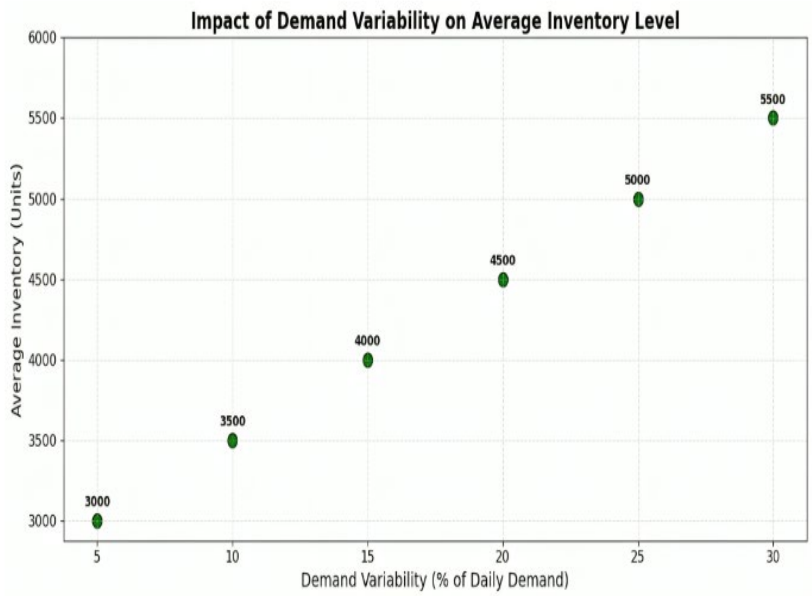

Figure 8. Average inventory vs demand variability

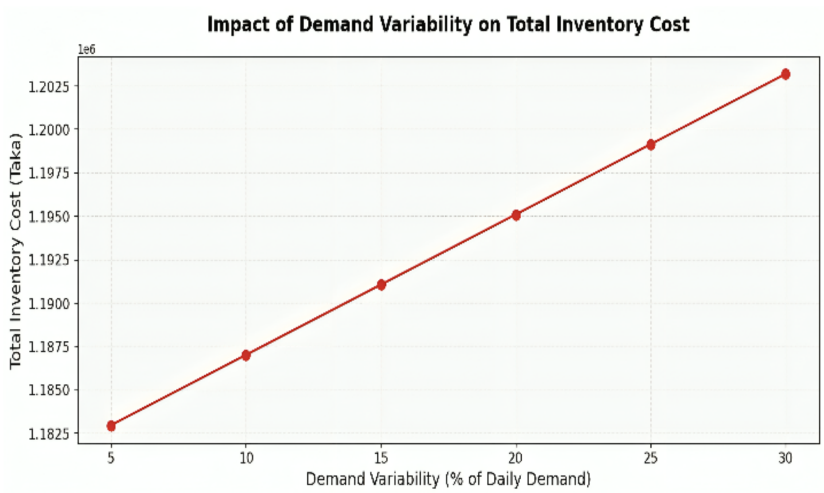

Figure 9. Total cost (taka) vs demand variability

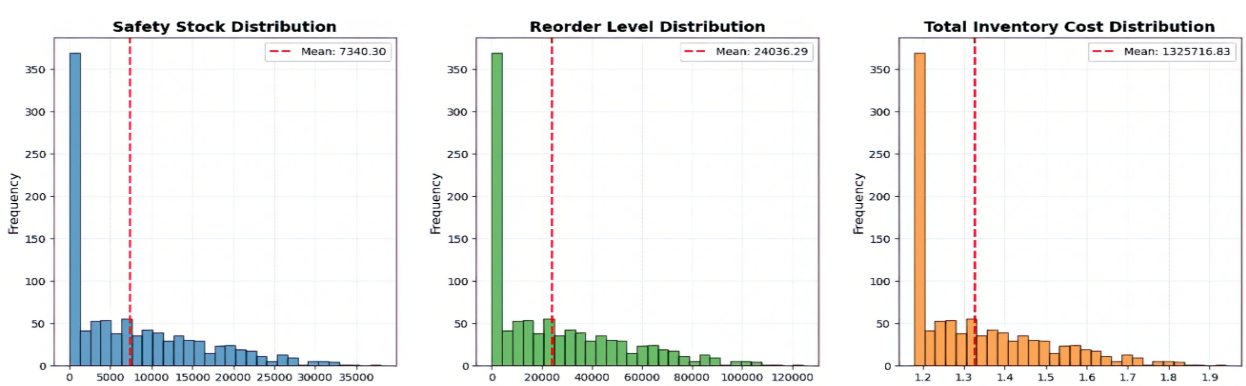

Figure 10. Distributions of inventory metrics using monte carlo simulation

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6. Discussion

This study examined how well linear regression and exponential smoothing predict demand in the pharmaceutical industry, focusing on the diabetes drug GLYMIN. While both approaches produced precise demand forecasts, linear regression surpassed the other with lower error metrics, such as MAD, MSE, and MAPE. Because of its accuracy, it was able to reflect the upward trend in GLYMIN sales better and comply with inventory management regulations. By incorporating linear regression forecasts into an inventory model, the study produced ideal operational parameters like EOQ, safety stock, and reorder levels. Sensitivity analysis demonstrated how lead time and demand variability significantly affect important inventory parameters, such as safety stock, reorder level, and average inventory. Monte Carlo simulation shows variability in inventory metrics, reflecting uncertainty in demand or lead times to aid inventory optimization.

7. Conclusion and future scope

This research underscores the importance of integrating demand forecasting techniques with inventory models in the pharmaceutical industry. Linear regression performed better than exponential smoothing among the tested methods, which makes it a suitable option for demand prediction in this context. Applying these forecasts to an inventory model demonstrated improvements in cost efficiency and supply reliability. There is a lot of potential for optimizing supply chain operations, reducing expenses, and enhancing service delivery in the pharmaceutical industry by integrating demand forecasting and EOQ for inventory management. Stochastic modeling, AI, real-time data tracking, and collaborative forecasting are all important fields where innovation can keep pushing the envelope of what is feasible. Pharmaceutical companies can achieve more effective, responsive, and sustainable inventory management systems by addressing the particular difficulties faced by the industry, such as perishability, regulatory complexity, and demand variability. However, the analysis was based on a limited dataset, which may restrict the breadth and reliability of the results across different contexts. The analysis could include a larger dataset to increase forecasting accuracy and offer a more in-depth understanding of demand trends. Future research could use a hybrid model and a larger dataset to recognize seasonality and nonlinear relationship trends in demand.

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