



## A Comparative Study of AI-Based and Traditional Demand Forecasting Methods in FMCG Supply Chains

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### 1. Introduction

Write the content here. Line spacing 1.15 In the Fast Moving Consumer Goods (FMCG) industry, there is no room for error whatsoever. Products such as milk, meat, soap, and snacks have an exceptionally short lifespan, and the market is highly unpredictable as people's preferences can change at any time. Under such circumstances, accurately calculating the demand requires more than just ticking the boxes. Accurate demand forecasting allows one to avoid wastage, ensure profitability, and develop a strong supply chain infrastructure capable of handling any situation. Conventional techniques such as moving averages, exponential smoothing, and ARIMA have always been preferred among supply chain experts due to their simplicity and the added advantage of comprehending how they operate. Nonetheless, we currently operate in an era where markets behave more abruptly and unpredictably than ever before. And this is where the application of Artificial Intelligence and Machine Learning takes place by utilizing advanced machine learning models like LSTM or Gradient Boosting, thereby changing everything regarding the forecasting of demand. Traditional demand analysis models that have been based on linear computation based on past data cannot be applied here, as the AI model can analyze very large amounts of varied data.

This is precisely what the research will examine. To what extent are the forecasts generated by the machine learning algorithms more reliable than those generated by the conventional approaches? It certainly appears more than just an empty promise. What the research will attempt to substantiate is that the advantage of the new techniques is that they can recognize the complexity inherent in the environment and adjust accordingly, say, via Permutation Complexity, which indicates nonlinearity and unpredictability of the sales trends. This study will explore the occasions when conventional approaches would be sufficient, and occasions when only AI technologies could prevent wastage and inventory management.

## 2. Review of Literature

1. Ms Jesca Paidamoyo Dambanemuya (2025) Enhancing Demand Forecast Accuracy for FMCG Products Using SupplySeers Time Series Models and Permutation Complexity:

The purpose of this research paper was to examine the effectiveness of SupplySeers' time-series model and the principle of permutation complexity when making forecasts of FMCG products' demand. It has been discovered that modern methods, including SupplySeers time series models, outperformed traditional methods, such as Holt-Winters models, because they were capable of detecting non-linear seasonality.

2. Hatim Kagalwala (2025) Predictive Analytics in Supply Chain Management: The Role of AI and Machine Learning in Demand Forecasting: This study was performed with the objective of understanding the impact of artificial intelligence and machine learning in reducing demand uncertainty issues. It has been observed that the AI model proves to be a lot more effective compared to other models since it allows us to make use of real-world information as well as external factors impacting demand.
3. Afeez Adeyemo (2025) Optimizing Supply Chain Management through AI-Powered Demand Forecasting: An investigation of the ways to use AI-based algorithms such as LSTM and ensembles into SCM was conducted by the researcher. According to the results obtained, the usage of AI significantly reduced forecasting errors making MAPE equal to 6.8%, while it was 12.5% for ARIMA. The result was a 14% decrease in stockouts and 18% decrease in overstocking rates.
4. GV Radhakrishnan (2025) AI-Based Demand Forecasting System for Supply Chain Optimization: The combined approach of LSTM and ensemble learning methods improved prediction accuracy by 25%, resulting in lower inventory costs and higher order completion rates.
5. Pradeep Verma (2024) Transforming Supply Chains Through AI: Demand forecasting, inventory management, dynamic optimization: AIs such as LSTM and gradient boosting always performed better than traditional models when it came to seasonality and peaks, providing substantially smaller RMSE values.
6. Kontopoulou (2023) A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks: This literature review study compared ARIMA with several machine learning approaches in different domains. According to the researchers, although ARIMA is strong when dealing with linear time series, artificial intelligence (AI) approaches such as LSTM show better predictive ability when dealing with non-linear situations.
7. Arnab Mitra (2022) A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Hybrid Machine Learning Technique: The authors presented a new hybrid technique that uses the Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and linear regression (LR) techniques. It was observed that the hybrid model performed better than individual models, such as ANN and ARIMA, with an incredible R-squared value of 0.9551.
8. Mario Angos Mediavilla (2022) Review and analysis of artificial intelligence methods for demand forecasting in supply chain management: In this paper, trends in AI algorithms that have been employed in forecasting for SCM from 2017 to 2021 were examined. It was observed that there is a clear trend towards adopting Deep Learning algorithms (e.g., LSTM) due to the inability of conventional statistical approaches to deal with high dimensionality data.

- 9. Sai Krishna Chitanya Tulli (2020) Comparative Analysis of Traditional and AI-based Demand Forecasting Models: The objective was to compare traditional models (ARIMA) against AI models (LSTM, Random Forest) across retail and manufacturing. The findings highlighted that while traditional models are computationally cheaper and easier to interpret, AI models excel in handling non-linear, high-dimensional data, offering superior accuracy in volatile markets.
- 10. Elcio Tarallo (2019) Machine Learning in Predicting Demand for Fast-Moving Consumer Goods: This exploratory research sought to identify the benefits of ML in sales forecasting for short shelf-life products. The study concluded that ML techniques surpass traditional statistical accuracy, leading to improved inventory balancing and reduced stockout rates at points of sale

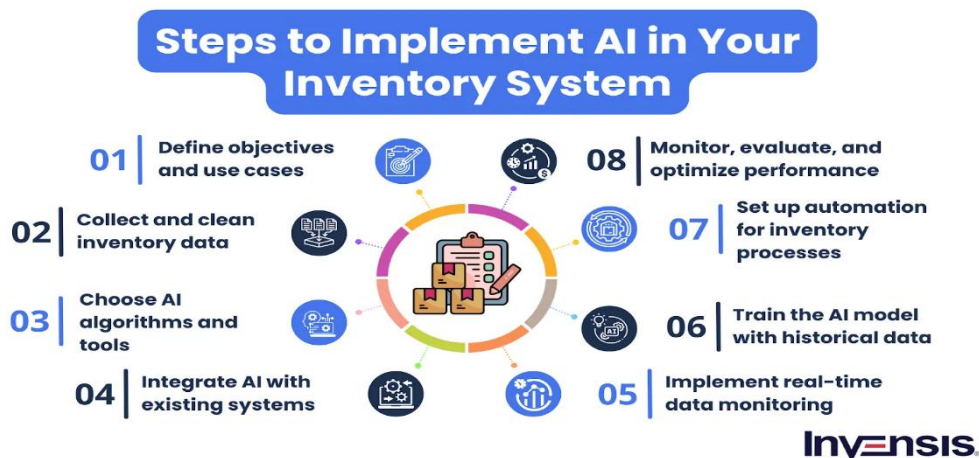
### 3. Research Gap

While the existing literature extensively compares AI and traditional models in broad terms, several specific gaps remain that The comparison is grounded in addressing:

- 1. Complexity-Aware Selection: Most studies apply a ‘one-size-fits-all’ approach to model selection. Surprisingly, most studies still rely on using Permutation Complexity as a pre-processing metric to categorize FMCG products based on their demand chaos (entropy) before selecting a forecasting model.
- 2. Hybridization in FMCG: While hybrid models (like RF-XGBoost-LR) have been tested in general retail, there is limited empirical evidence validating specific architectures like the "SupplySeers" engine against established baselines (like Holt-Winters) specifically for high-volatility FMCG product lines.
- 3. Scalability vs. Interpretability: Few studies adequately address the practical trade-off between the superior accuracy of "black box" Deep Learning models and the interpretability required for supply chain managers to trust these systems in daily Soperations.

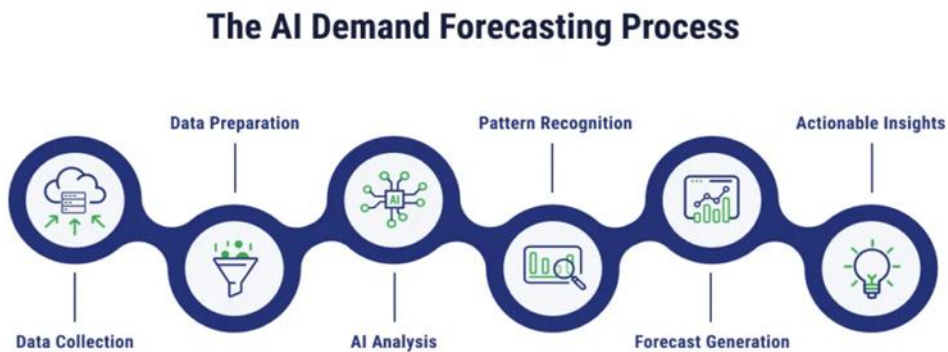
### 4. Recent trends in demand forecasting using AI in supply chain

Reducing stockouts, increasing SKU-level forecast accuracy, and controlling demand volatility are some of the initial goals of AI-based demand forecasting in the FMCG supply chain. Large amounts of organized and unstructured data, including as past sales, seasonal trends, point-of-sale information, and current market



signals, are utilized by these systems. Given that forecasting is contingent upon advanced techniques such as predictive analytics and machine learning, it is vital to select appropriate AI algorithms during the process of forecasting. The inclusion of real-time monitoring becomes important owing to the fast pace at which FMCG products evolve. Different from conventional forecasting techniques, which mainly depend on historical data and limited internal data sources, AI-based systems factor in different types of information and external variables such as weather patterns and market demands.

The use of artificial intelligence makes it possible for forecasting software to automatically cleanse, organize, and structure huge amounts of data, thereby improving the accuracy of



data. The traditional forecasting models depend on humans to make preparations to a great extent. In this case, while the conventional methods use basic statistical tools such as trends analysis and moving average methods, artificial intelligence analyzes large quantities of data to discover hidden correlations and patterns that are nonlinear. The artificial intelligence system can make dynamic changes to estimations based on recurrent demands caused by seasonality, marketing, and customer behavior. Traditional methods of predicting demand fail to achieve these due to their tendency to come up with unrealistic predictions based on assumptions that future demands will be similar to those observed in the past. Demand predictions become more realistic and accurate to the AI-based forecasting solutions since the latter enable them to be updated in real-time. It is difficult for the traditional forecasting models to be useful for managing products whose demand fluctuates rapidly due to the relatively long period within which they are updated.

## 5. Research Methodology

### a. Problem Statement:

A faulty demand forecast in the supply chain management of FMCGs has the potential to create a snowball effect within the processes of business, resulting in inefficiencies that become even more pronounced as a result. The failure of demand forecasts results in what is referred to as the "bullwhip effect" in which stockouts, high expenses related to overproduction, and the wastage of perishable items occurs. Conventional techniques such as moving averages and ARIMA do not succeed in accounting for demand trends that are complex and non-linear in nature.

b. Research Objective: The primary objectives of this study are:

- Investigate the effect of using artificial intelligence-based models for FMCG demand forecasting, such as SupplySeers, LSTM, XGBoost, compared to conventional methods like ARIMA, Holt-Winters.
- Investigate the importance of Permutation Complexity in improving forecasting accuracy through classification of time-series data according to volatility.
- Investigate the impact of artificial intelligence forecasting on inventory management, particularly minimizing stockout and overstock conditions.

### **c. Sources of Data:**

The current research will employ a descriptive research design that is supported by secondary sources of data. The data used for analysis was acquired from different sources like academic journals (including the International Journal for Multidisciplinary Research, Procedia CIRP, and Future Internet), academic papers, and reports relating to supply chain management and artificial intelligence.

### **d. Scope of Study:**

The investigation is concerned exclusively with the FMCG industry, which includes product categories like food, drinks, and cosmetics. The model's accuracy is assessed in terms of its ability to predict future values using common error measures like RMSE, MAE, and MAPE. Moreover, the study seeks to apply these models in practice to improve inventory management and decision-making processes.

### **e. Limitation of Study**

Data quality and accessibility play a crucial role in the effectiveness of the AI algorithms that were examined in this study. The presence of any gaps or errors in the data can have an immense effect on the results obtained through model training and forecasting since it relies heavily on secondary data. Poor data quality can lead to biased results, which makes AI models less valuable and reliable. Apart from data issues, more sophisticated algorithms, such as Long Short-Term Memory (LSTM), require additional computing resources and extensive time to learn, which may not be easily available to all organizations, especially smaller ones. Thus, it would add to the cost of implementing AI models for businesses. Furthermore, the study's findings might be limited due to the reliance on Secondary data. Consumer behavior, the market environment, economic factors, and other issues can affect the results of model testing depending on the area or particular type of product studied. In summary, even though the efficiency of AI algorithms in predicting customer behavior is extremely high, it is still dependent on data quality and availability

## **6. Findings**

Several practical findings of the comparative analysis of the chosen models can be summarized as follows:

1. **A Superior Performance of AI-Based Models:** Predictive accuracy was higher when AI-based models such as SupplySeers architecture and long-short-term memory models were used in comparative experiments. Thus, while MAPE generated by traditional models including ARIMA and Holt-Winters was approximately 20-21%, SupplySeers had a considerably lower MAPE equaling approximately 10.29%. This finding demonstrates the possibility of capturing non-linear trends and seasonalities, which traditional models fail to do.
2. **Importance of Model Complexity:**The research discovered an inverse relationship between Permutation Complexity (PC) and predictive accuracy. While highly complex time series could not be adequately predicted by traditional models due to their linearity, non-linear AI-based models

managed to generate accurate forecasts. Therefore, from the standpoint of supply chain planning, model selection is crucial in consideration of demand complexity rather than demand volume. Application of a PC as a 'filter' helped to select an appropriate model for the product at hand.

3. **Operational Efficiency:** The use of AI-based forecasting systems has been found to offer real operational efficiencies. The hybrid models used by combining the statistical base line models with machine learning residuals cut down forecast error rates by up to 25%. On an operational level, this increase in forecast accuracy is likely to result in a 20-30% decline in the cost of inventory holding.

## 7. Suggestions

Based on the research findings, the following recommendations are proposed for FMCG stakeholders:

- **Embrace Complex Models:** Firms cannot adopt a blanket approach to modeling; rather, they need to estimate the Permutation Complexity of the sales of individual products. Simpler approaches must be applied to complex products, while complicated AI-based techniques can be employed to analyze volatile products..
- **Focus on Data Infrastructure:** If an organization wishes to harness the full benefits of AI, it should not just rely on its sales records. Investing in data infrastructure that is capable of collecting real-time data from outside (like promotions, weather changes, economy) is critical because bad data quality is the biggest impediment to AI effectiveness.
- **Implement Hybrid Models:** Instead of deciding to go either "traditional" or "AI," companies must adopt a hybrid approach (such as SupplySeers or RF-XGBoost-LR model). This allows organizations to leverage statistical insights and at the same time utilize machine learning for residual errors.

## 8. Conclusion

When implementing AI technology in the supply chain management of FMCGs, there will be a change from being reactive to proactive or optimization. As illustrated in the comparison study, while conventional models like ARIMA can work well where the environment is relatively stable and the level of complexity is lower, they fail to meet the requirements of modern dynamic business environments. The models incorporating artificial intelligence (AI) techniques, as well as the Permutation Complexity models, provide a completely new insight. The capacity of capturing nonlinearity and adapting to changes makes the use of the advanced models useful in helping businesses attain an efficient way of minimizing the bullwhip effect without wastage. It is clear from the above analysis that the study proves the need for the industry to evolve in its forecasting techniques by considering the complexity of AI in the future.

As the FMCG markets become increasingly unpredictable, it will not matter whether AI will be embraced or not but rather how smart the integration of the same will be.

## Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

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