

A Hybrid Explainable Artificial Intelligence and Artificial Neural Network Framework for Multi-Horizon Demand Forecasting and Sustainable Inventory Optimization under Demand Uncertainty

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Abstract: Accurate demand forecasting and efficient inventory management are essential for resilience and sustainability in modern supply chains. Traditional forecasting methods often fail to capture demand patterns and give limited insight into decision-making especially when markets are dynamic and uncertain. This study introduces a Hybrid Explainable Artificial Intelligence (XAI) and Artificial Neural Network (ANN) Framework for multi-horizon demand forecasting and sustainable inventory optimization under demand uncertainty. The framework uses an Artificial Neural Network to model demand behavior and combines it with Explainable AI tools, such as SHAP (SHapley Additive exPlanations) to explain prediction results and highlight which demand-influencing factors are most important. The resulting multi-horizon demand forecasts are then fed into an inventory optimization module that finds the best inventory policies to reduce holding ordering and stockout costs while keeping service levels at the desired level. The framework is tested on retail demand datasets and compared with typical statistical models and cutting-edge machine learning methods such as ARIMA, Random Forest and Long Short-Term Memory (LSTM) networks. Model performance is measured with forecasting metrics like RMSE, MAE, MAPE and R^2 well as inventory-related indicators such as total inventory cost, service level, inventory turnover and stockout frequency. Experimental results show that the hybrid framework raises demand forecasting accuracy improves inventory decision quality and supplies interpretable advice for supply chain practitioners. By blending power, with explainable decision support this approach helps create trustworthy AI-enabled inventory management systems that support sustainable and data-driven supply chain operations. The results give guidance to inventory managers and policymakers who want to boost operational efficiency, cut waste and strengthen supply chain resilience when business conditions are uncertain.

Keywords: Artificial Neural Network (ANN); Explainable Artificial Intelligence (XAI); Demand Forecasting; Multi-Horizon Forecasting; Sustainable Inventory Management; Supply Chain Management; Inventory Optimization; Demand Uncertainty; SHapley Additive exPlanations; Decision Support Systems

1. Introduction

Given the increasing complexity in the functioning of global supply chains and the fast-changing customer demands, it is essential to be able to forecast demand and control inventory in order to remain competitive and sustainable. Demand forecasting and management of inventories are hindered by such challenges as volatility of demand, risks of supply disruptions, shortened product life cycles, and changes in the operating environment, leading



to potential shortage of stocks, surplus of stocks, and increased costs. Therefore, it becomes vital to look for smarter ways that will help to provide accurate forecasts and make efficient and sustainable decisions on inventories.

Demand forecasting is a basis for making decisions on inventory, scheduling of production, procurement, and distribution management. With accurate demand forecasts, one may maintain proper inventories and avoid such issues as high costs associated with them, poor customer service, and increased risks. There are many methods of forecasting used by businesses, for instance, moving averages, exponential smoothing, and Autoregressive Integrated Moving Average (ARIMA). The main advantage of these statistical methods lies in their ease of use. However, it is not easy for these methods to catch relationships between variables.

Artificial Intelligence (AI) has become a tool that can solve many problems by using advanced learning from data. Among the AI methods Artificial Neural Networks (ANNs) stand out because they can model difficult, nonlinear patterns and give very accurate demand forecasts for many fields. ANNs can learn from data without needing strict statistical rules so they are good for predicting when markets change quickly and when there is uncertainty. With these strengths people often criticize ANN models because they are hard to understand. Their inner workings are mostly hidden from managers and practitioners. This lack of clarity reduces trust in forecasts and makes it hard to use them in important supply chain decisions.

To make models clearer Explainable Artificial Intelligence (XAI) has attracted a lot of interest lately. XAI methods, like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) give easy-to-understand explanations of predictions by showing how much each input variable contributes. These tools increase the trustworthiness and usefulness of AI by letting decision-makers see not what the model says but also why it says that. Adding explainability to forecasting models is a move toward reliable and human-friendly AI in supply chain work.

Many papers have looked at AI for demand forecasting or inventory planning on their own. Only a few have combined explainable predictions with sustainable inventory choices in one support system. Most studies mainly aim to make forecasts more accurate and spend time on turning those numbers into real inventory rules when demand is uncertain. Also the need for forecasts that cover medium and long periods at the same time is still not well studied. Because of these gaps this work proposes a Hybrid Explainable Artificial Intelligence and Artificial Neural Network Framework for Multi-Horizon Demand Forecasting and Sustainable Inventory Optimization when demand is uncertain. The new framework mixes the prediction power of Artificial Neural Networks with Explainable AI tools to produce both precise and understandable demand forecasts for many time periods. After forecasting the results feed into an inventory optimization part that finds stock rules. These rules aim to lower inventory costs while keeping high service levels even when demand is unclear. By putting together prediction skill, clear explanations and inventory planning, in one package this study helps move transparent, dependable and sustainable AI tools for today's supply chain work.

2. Literature Review

Artificial Intelligence (AI) has fundamentally transformed supply chain management by enabling organizations to leverage large-scale data for predictive analytics, intelligent decision-making, and operational optimization. AI technologies have been increasingly applied to procurement, production planning, logistics, warehouse management, inventory control, and demand forecasting, significantly improving supply chain agility and resilience. Recent review studies indicate that machine learning and deep learning techniques have become central to modern supply chain analytics because of their ability to model complex nonlinear relationships and process heterogeneous data sources more effectively than conventional analytical approaches (Kosasih et al., 2024; El Aouifi et al., 2024). However, despite the rapid adoption of AI, many existing implementations remain fragmented, where forecasting, inventory planning, and decision support are developed independently rather than within an integrated intelligent framework.

Demand forecasting has received considerable attention because it directly influences procurement decisions, production scheduling, inventory replenishment, and customer service. Traditional forecasting techniques, including

moving averages, exponential smoothing, and ARIMA, have been widely adopted due to their computational simplicity. Nevertheless, these methods generally assume linearity and stationarity, limiting their capability to capture the nonlinear, dynamic, and uncertain characteristics of modern retail and manufacturing demand. Artificial Neural Networks (ANNs) have therefore emerged as one of the most effective alternatives because they can learn complex input-output relationships without requiring strict statistical assumptions. Numerous empirical studies have demonstrated that ANN-based models outperform conventional forecasting techniques in terms of forecasting accuracy, particularly when demand patterns are influenced by seasonality, promotions, holidays, and external economic variables. More recently, hybrid deep learning architectures incorporating LSTM, CNN, GRU, and Transformer networks have further enhanced forecasting performance by learning both temporal dependencies and nonlinear feature interactions (El Aouifi et al., 2024).

Although the Artificial Neural Network (ANN) has demonstrated high predictive accuracy for demand forecasting, it lacks explainability and interpretability, which has inhibited its adoption in the supply chain field. Firms' supply chain managers were not willing to use the forecast result generated from an unexplainable model. The issue of model explainability has spurred the development of the concept of Explainable Artificial Intelligence (XAI) in the literature, where the Shapley value and Local Interpretable Model-Agnostic Explanations (LIME) were used to identify the impact of each variable on the forecasting model's output. Researchers argue that explainability has become more than just a visualization tool for model interpretability; instead, it should be considered an essential element of supply chain decision support systems (Kosasih et al., 2024).

In parallel with forecasting analytics, inventory management has transitioned from simple economic order quantity (EOQ), reorder point, and safety stock formulas to an integrated system driven by data and insights (Chopra & Meindl, 2016). However, classical inventory management theories are not appropriate for demand planning under volatile, unpredictable, and uncertain market conditions (Seyedan et al., 2023; He et al., 2026). In addition, scholars have advocated for using predictive analytics and machine learning algorithms for enhanced inventory decisions to mitigate shortages and surplus while boosting supply chain sustainability (Haldar et al., 2026). Specifically, AI-based demand forecasting and inventory optimization tools have been proposed to address waste reduction and sustainability while supporting firms' operations in the face of demand volatility and uncertainty (Haldar et al., 2026).

Nevertheless, forecasting analytics and inventory management have been identified as areas needing further research attention due to the limitation of the literature in this regard. First, the majority of papers have focused on how to develop highly-accurate predictive models in supply chains while neglecting the interpretation issue. Second, explainability has been integrated with the forecast algorithms to enhance model transparency, but inventory management has not been considered. Third, demand forecasting and inventory optimization were often viewed as independent sequential processes, but they need to be combined into an intelligent system to facilitate effective, efficient, and accurate decision-making. Fourth, although firms may require multiple time horizons' forecasts for supply chain planning at various levels and functions, little is known about the development of multi-horizon demand forecasting analytics for integrated and sustainable inventory management.

To address the research-identified gaps and limitations, this study aims to propose a Hybrid Explainable Artificial Intelligence and Artificial Neural Network Framework for Multi-Horizon Demand Forecasting and Sustainable Inventory Optimization under Demand Uncertainty. Unlike existing works, the current study attempts to combine ANN-based accurate prediction and explainable AI for interpretable inventory decisions to facilitate firms' simultaneous attainment of demand forecasting accuracy and inventory sustainability under demand volatility and uncertainty. The anticipated contribution of this research endeavor lies in its theoretical and practical significance. On the theoretical front, this work will advance the frontier of knowledge in explainable AI in general and supply chain analytics in particular. On the practical front, the proposed hybrid framework will offer a novel integrated intelligent decision support system for inventory managers in dynamic business settings.

3. Research Gap and Contributions

The literature demonstrates substantial progress in the application of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques for supply chain management, particularly in demand forecasting and inventory optimization. Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Random Forest, Gradient Boosting, and Transformer-based architectures have consistently outperformed conventional statistical forecasting techniques in capturing nonlinear demand patterns and improving forecasting accuracy (Douaioui et al., 2024; El Aoufi et al., 2024; Makridakis et al., 2022). Furthermore, Explainable Artificial Intelligence (XAI) techniques, including SHAP and LIME, have recently emerged as effective approaches for improving the transparency and interpretability of black-box machine learning models, thereby increasing managerial trust in AI-assisted decision-making (Kosasih et al., 2024; Lundberg & Lee, 2017; Ribeiro et al., 2016).

Despite these advancements, several important limitations remain in the existing literature. First, the majority of AI-based demand forecasting studies primarily emphasize prediction accuracy while paying relatively limited attention to the interpretability and explainability of forecasting models. Consequently, many high-performing AI models remain difficult for supply chain managers to understand and validate before deployment in operational environments (Kosasih et al., 2024; Zhu et al., 2025).

Second, although numerous studies have investigated inventory optimization using traditional mathematical models or machine learning algorithms, forecasting and inventory optimization are generally treated as two independent research problems. The forecasting model typically generates demand predictions, whereas inventory decisions are optimized separately without considering the uncertainty and explainability associated with AI-generated forecasts (Babai et al., 2022; Silver et al., 2016). Such fragmented approaches often reduce the practical effectiveness of intelligent inventory management systems.

Third, recent advances in Explainable Artificial Intelligence have primarily focused on interpreting prediction models rather than integrating explainability into downstream operational decisions such as inventory replenishment, reorder point determination, safety stock estimation, and procurement planning. As a result, the practical value of XAI within inventory management remains relatively underexplored, particularly in sustainable supply chain applications (Jauhar et al., 2025; Kosasih et al., 2024).

Another important limitation concerns forecasting horizons. Most published studies concentrate on single-period or short-term forecasting, whereas modern supply chains require accurate predictions across multiple planning horizons to support operational, tactical, and strategic decision-making. Multi-horizon demand forecasting enables organizations to coordinate procurement, production scheduling, transportation planning, warehouse operations, and inventory replenishment more effectively under uncertain market conditions. Nevertheless, relatively few studies have proposed unified frameworks capable of simultaneously addressing multi-horizon forecasting and sustainable inventory optimization (Douaioui et al., 2024; Makridakis et al., 2022).

Moreover, sustainability considerations remain insufficiently integrated into AI-enabled inventory management. Existing optimization approaches frequently focus on minimizing inventory costs while overlooking broader sustainability objectives, including waste reduction, efficient resource utilization, supply chain resilience, and environmentally responsible inventory policies. With increasing emphasis on sustainable supply chain management and Industry 5.0 principles, there is a growing need for intelligent decision-support systems that simultaneously optimize economic performance, operational efficiency, and sustainability outcomes (Choi et al., 2018; Haque, 2025).

To address these limitations, this study proposes a Hybrid Explainable Artificial Intelligence and Artificial Neural Network Framework for Multi-Horizon Demand Forecasting and Sustainable Inventory Optimization under Demand Uncertainty. The proposed framework integrates ANN-based nonlinear demand forecasting with Explainable Artificial Intelligence to generate transparent and interpretable predictions across multiple forecasting horizons. These predictions are subsequently incorporated into an inventory optimization module that determines sustainable inventory policies by minimizing ordering costs, holding costs, and stockout risks while maintaining desired service levels. Unlike existing approaches that separately address forecasting accuracy, explainability, and inventory optimization, the proposed framework combines these components within a unified intelligent decision-support architecture.

The primary contributions of this study are fourfold. First, it develops a hybrid AI framework that integrates ANN and XAI for transparent multi-horizon demand forecasting. Second, it establishes a unified decision-support framework linking demand forecasting directly with sustainable inventory optimization. Third, it incorporates explainable AI into inventory-related decision-making, thereby improving managerial trust and model interpretability. Finally, it provides practical insights for supply chain managers by supporting intelligent, transparent, and sustainable inventory decisions under demand uncertainty.

4. Research Framework and Methodology

The study proposed an integrated research framework which unified Artificial Neural Network (ANN) based multi-horizon demand forecasting, Explainable Artificial Intelligence (XAI) and sustainable inventory optimization. The historical demand data and influencing factors were utilized to train an artificial neural network model. The forecasting results were further processed by SHAP-based analysis to interpret the model. Then a set of optimal inventory policies were determined based on the forecasted demand to make a balance between inventory cost and environmental impact under demand uncertainty. The performance of the framework was measured by forecasting accuracy, service level, inventory cost, turnover and stockout-related indicators.

4.1 Integrated Explainable AI – Artificial Neural Network Framework.

The increasing complexity of modern supply chain ecosystems, driven by demand uncertainty, shortened product life cycles, global sourcing, and rapidly changing customer preferences, has necessitated the development of intelligent decision-support systems capable of simultaneously improving forecasting accuracy, operational efficiency, and managerial transparency. Although Artificial Intelligence (AI) has significantly enhanced supply chain analytics through advanced predictive modelling techniques, most existing solutions remain confined to isolated forecasting or inventory management tasks. Consequently, the lack of integration between predictive intelligence, explainability, and inventory optimization often limits their practical applicability in real-world business environments. To overcome these challenges, this study develops an Integrated Explainable Artificial Intelligence–Artificial Neural Network (XAI–ANN) Framework that establishes a unified decision-support architecture for multi-horizon demand forecasting and sustainable inventory optimization under demand uncertainty.

The framework is designed around the principle that accurate forecasting alone is insufficient for effective supply chain management. Decision-makers require not only reliable demand predictions but also transparent explanations of the factors influencing those predictions and optimized inventory policies that translate predictive insights into operational actions. Accordingly, the proposed architecture integrates three complementary analytical components: an Artificial Neural Network (ANN) for nonlinear demand forecasting, an Explainable Artificial Intelligence (XAI) module for interpreting model behaviour, and an inventory optimization module for determining economically and operationally efficient replenishment strategies. Unlike conventional sequential approaches in which forecasting and inventory optimization are treated as independent processes, the integrated framework establishes a continuous information flow that enables forecasting outputs to directly support inventory decisions while maintaining model transparency throughout the decision-making process.

The conceptual architecture consists of five interconnected modules: data acquisition and preparation, predictive modelling, explainability analysis, inventory optimization, and performance evaluation. These modules are linked through a structured analytical workflow in which the output of each stage serves as the input for the subsequent stage, thereby creating an end-to-end intelligent supply chain decision-support system. The modular architecture provides flexibility for implementation across different industrial domains, including retail, manufacturing, healthcare, logistics, and e-commerce, while allowing future integration of additional forecasting algorithms or optimization techniques without modifying the overall framework. The first module focuses on acquiring historical demand information together with operational and contextual variables that influence purchasing behaviour. In addition to historical sales records, the framework incorporates explanatory variables such as inventory availability, supplier lead time, procurement cost, promotional campaigns, seasonal effects, public holidays, pricing strategies, customer demand variability, and macroeconomic indicators where available. By integrating multiple demand-influencing factors, the

framework captures complex nonlinear relationships that are often overlooked by conventional statistical forecasting models. This multidimensional representation improves the capability of the predictive model to adapt to dynamic market conditions and evolving customer behaviour.

Following data acquisition, the framework performs comprehensive preprocessing to improve data quality and analytical reliability. Real-world supply chain datasets frequently contain missing observations, duplicate transactions, inconsistent attribute values, and anomalous records that adversely affect predictive performance. Therefore, preprocessing procedures including data cleaning, missing value imputation, outlier treatment, normalization, and categorical encoding are performed before model development. Subsequently, feature engineering generates additional explanatory variables, including lagged demand, rolling averages, seasonal indices, trend indicators, and promotional effects, enabling the learning algorithm to capture temporal and contextual dependencies more effectively. Feature selection techniques are then employed to eliminate redundant variables and reduce computational complexity while preserving predictive capability.

The processed dataset is supplied to an Artificial Neural Network that serves as the predictive core of the framework. The ANN is designed to learn nonlinear functional relationships between demand drivers and future demand through iterative optimization using supervised learning. Unlike traditional forecasting techniques that rely on predefined assumptions regarding demand distributions, the ANN automatically extracts hidden patterns from historical observations by adjusting network parameters during training. The model is configured to generate forecasts across multiple planning horizons, thereby supporting short-term operational decisions, medium-term tactical planning, and long-term strategic resource allocation within a single unified architecture.

Despite their superior predictive capability, Artificial Neural Networks are frequently criticized for their limited interpretability. High forecasting accuracy alone is often insufficient for practical deployment because supply chain managers require transparent explanations before incorporating AI-generated recommendations into procurement and inventory decisions. To address this challenge, the framework incorporates an Explainable Artificial Intelligence module immediately following the forecasting stage. The explainability module applies post hoc interpretation techniques to quantify the contribution of individual input variables to each forecasting outcome while simultaneously identifying the global importance of demand drivers across the complete dataset. This additional analytical layer transforms the ANN from a black-box predictor into a transparent decision-support tool capable of providing both accurate forecasts and interpretable managerial insights.

The explainable forecasting outputs are subsequently integrated into an inventory optimization module responsible for determining economically efficient and sustainable replenishment policies. Rather than relying exclusively on historical averages, the optimization process utilizes AI-generated forecasts to estimate inventory control parameters, including Economic Order Quantity (EOQ), reorder point, safety stock, replenishment frequency, and inventory review intervals. The optimization objective is to minimize the combined costs associated with ordering, inventory holding, and stock shortages while maintaining desired service levels and reducing inventory waste. By directly linking forecasting intelligence with inventory optimization, the framework enables organizations to transform predictive information into practical operational decisions, thereby improving responsiveness, reducing uncertainty, and enhancing overall supply chain resilience.

The final component of the framework performs comprehensive performance evaluation by assessing both forecasting quality and inventory effectiveness. Forecasting performance is evaluated using statistical accuracy measures, whereas inventory performance is assessed using operational indicators such as inventory turnover, fill rate, service level, stockout frequency, and total inventory cost. Comparative evaluation against conventional forecasting models and existing inventory management approaches further demonstrates the effectiveness of the integrated framework in improving predictive accuracy, decision transparency, and operational performance.

Overall, the Integrated Explainable AI–Artificial Neural Network Framework establishes a unified intelligent decision-support architecture that bridges the gap between predictive analytics and inventory management. By integrating advanced neural network forecasting, explainable artificial intelligence, and sustainable inventory

optimization within a single analytical workflow, the framework provides a robust foundation for data-driven supply chain decision-making under conditions of demand uncertainty. The subsequent sections present the detailed data preparation procedures, model formulation, optimization strategy, and evaluation methodology that operationalize this integrated framework.

4.2 Data Preparation

The study utilized secondary socioeconomic and demographic information from authoritative government sources, primarily the Census of India District Census Handbooks (DCHBs) published by the Office of the Registrar General & Census Commissioner, India, and the Directorate of Census Operations, West Bengal. The DCHBs provide detailed information on household characteristics, population, education, employment, housing, basic amenities, infrastructure, and rural–urban conditions at district and local administrative levels (Census of India, 2011).

The study considered three geographically and socioeconomically distinct districts of West Bengal, namely Howrah, Purba Medinipur, and Cooch Behar to capture variation in livelihood conditions. Howrah represents a comparatively urbanized and industrially influenced region, Purba Medinipur represents a predominantly rural and agriculture- and coastal-influenced livelihood environment, while Cooch Behar represents a predominantly rural northern Bengal setting with greater dependence on agriculture and allied activities. The secondary data were used to construct and contextualize the livelihood-related variables corresponding to the Human, Social, Natural, Financial, and Physical capital dimensions of the proposed framework.

The study utilized secondary socioeconomic and demographic information from the Census of India District Census Handbooks (DCHBs). A total of 3,200 households from Howrah, Purba Medinipur, and Cooch Behar were considered. The DCHB variables included household characteristics, education, employment, housing, basic amenities, infrastructure, and rural–urban conditions, which were mapped to the Human, Social, Natural, Financial, and Physical capital dimensions.

The effectiveness of any Artificial Intelligence (AI)-based forecasting model largely depends on the quality and consistency of the input data. Consequently, a comprehensive data preparation procedure was implemented to transform raw supply chain data into a structured and analytically reliable dataset suitable for model training and inventory optimization. The data preparation process comprised data acquisition, cleaning, pre-processing, normalization, feature engineering, and dataset partitioning to ensure robustness, generalization capability, and computational efficiency.

Let the complete dataset be represented as

$$D = (x_i, y_i), \quad i = 1 \text{ to } N \dots\dots(4.1)$$

where N denotes the total number of observations, $(x_i = [x_{i1}, x_{i2}, \dots, x_{im}]^T)$ represents an m dimensional feature vector associated with the i^{th} observation, and y_i denotes the corresponding demand value. The input feature space includes historical sales, inventory level, lead time, unit price, promotional activities, seasonal indicators, holidays, supplier performance, and other demand-influencing variables.

Raw datasets frequently contain missing observations, duplicated records, inconsistent attribute values, and anomalous measurements that may adversely affect the learning capability of Artificial Neural Networks. Therefore, missing numerical values were imputed using appropriate statistical methods, while duplicate and inconsistent records were removed during data cleaning. Extreme observations were identified using the Z-score criterion,

$$Z_i = \frac{x_i - \mu}{\sigma} \dots\dots\dots(4.2)$$

where μ and σ denote the mean and standard deviation of the corresponding variable. Observations satisfying $(|Z_i| > 3)$ were considered potential outliers and treated appropriately to minimize their influence on model training.

To improve numerical stability and accelerate ANN convergence, all continuous variables were normalized using Min–Max normalization,

where $x_i^* \in [0,1]$ represents the normalized feature value. This transformation ensures that variables measured on different scales contribute proportionately during network training and prevents features with large numerical ranges from dominating the optimization process.

Feature engineering was subsequently performed to enhance the predictive capability of the learning model. Additional explanatory variables, including lagged demand, moving averages, rolling standard deviations, seasonal indices, and promotional indicators, were generated to capture temporal dependencies and demand fluctuations. The transformed dataset was then partitioned into training, validation, and testing subsets according to

where the subsets are mutually exclusive, satisfying

A typical partition ratio of 70:15:15 (or 80:10:10 depending on dataset size) was adopted to facilitate model training, hyperparameter tuning, and unbiased performance evaluation.

The resulting pre-processed dataset provides a consistent, noise-reduced, and information-rich representation of demand-related variables, thereby establishing a reliable foundation for ANN-based multi-horizon demand forecasting and the subsequent explainable inventory optimization framework.

4.3 ANN-Based Multi-Horizon Demand Forecasting

Artificial Neural Networks (ANNs) were employed as the core predictive model due to their capability to learn complex nonlinear relationships between historical demand and multiple influencing factors. Unlike conventional statistical forecasting techniques, ANNs do not require predefined assumptions regarding data distribution and can effectively capture temporal and nonlinear demand patterns. In this study, a feedforward multilayer perceptron (MLP) trained using the backpropagation algorithm was adopted to generate multi-horizon demand forecasts for short-, medium-, and long-term inventory planning.

Let the input feature vector for the i th observation be represented as

where m denotes the number of explanatory variables. The ANN maps the input vector to multiple future demand values through a nonlinear function,

$$\hat{Y}_i = [\hat{y}_i^{(1)}, \hat{y}_i^{(2)}, \dots, \hat{y}_i^{(H)}] \dots \dots (4.8)$$

represents the predicted demand for H forecasting horizons, and θ denotes the network parameters consisting of weights and biases.

For each hidden neuron, the weighted summation is computed as

followed by a nonlinear activation function,

where $(\phi(z_j))$ represents the Rectified Linear Unit (ReLU) activation,

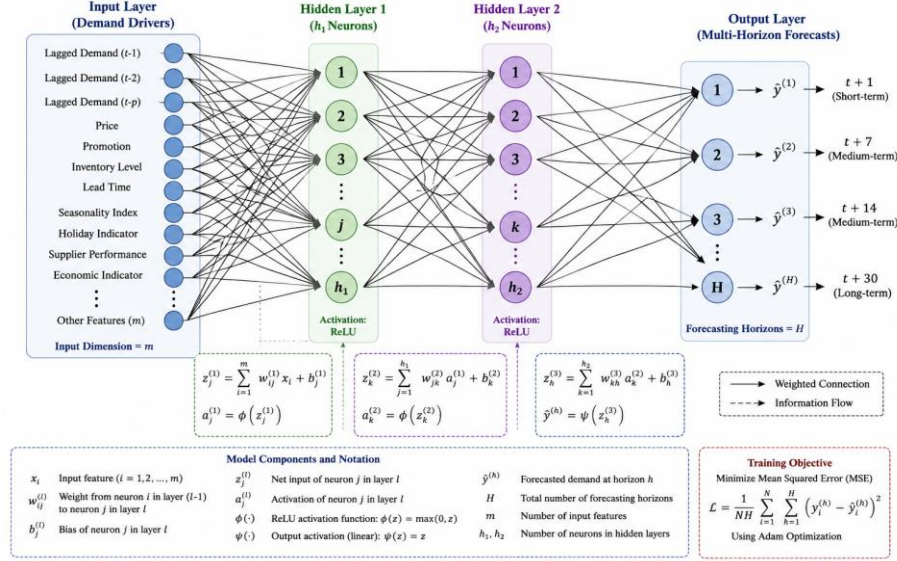
The output layer generates demand forecasts simultaneously for multiple planning horizons, enabling the model to support operational, tactical, and strategic inventory decisions within a unified forecasting framework.

Model training is performed by minimizing the Mean Squared Error (MSE) loss function,

where N is the number of training samples and H is the forecasting horizon. The network parameters are iteratively updated through backpropagation using the Adam optimization algorithm until convergence.

The trained ANN produces multi-horizon demand forecasts that capture nonlinear interactions among demand-driving variables. These forecasts serve as the primary input to the Explainable AI module, where prediction transparency and feature contribution are analysed before being utilized for sustainable inventory optimization.

Figure 2: Architecture of the ANN-Based Multi-Horizon Forecasting Model



4.4 Explainable AI-Based Inventory Optimization

The multi-horizon demand forecasts generated by the Artificial Neural Network (ANN) serve as the primary input for the inventory optimization module. Unlike conventional inventory control approaches that rely solely on historical demand statistics or deterministic assumptions, the proposed framework incorporates Explainable Artificial Intelligence (XAI) to enhance the transparency and reliability of inventory-related decisions. By integrating explainability with predictive analytics, the framework enables decision-makers to understand the contribution of demand-driving factors before determining optimal inventory policies, thereby improving trust, accountability, and operational robustness.

To interpret the ANN predictions, SHapley Additive exPlanations (SHAP) are employed to quantify the marginal contribution of each input feature to the forecasting outcome. For a prediction function $f(x)$, the SHAP value of feature i is computed as

$$\phi_i(f, x) = \sum_{S \subseteq F \setminus i} \frac{|S|! (|F| - |S| - 1)!}{|F|!} \dots \dots \dots (4.13)$$

where F denotes the complete feature set and S represents a subset of features. Positive SHAP values indicate features that increase the forecasted demand, whereas negative values represent factors that suppress demand. This feature-level interpretability enables managers to identify the key determinants of demand fluctuations and validate AI-generated forecasts before implementing inventory decisions.

The explainable forecasts are subsequently incorporated into an inventory optimization model that minimizes the total inventory cost while maintaining the desired customer service level. The objective function is expressed as

where TC denotes the total inventory cost, OC is the ordering cost, HC is the holding cost, and SC represents the shortage cost.

For a planning horizon of T periods, these components can be mathematically expressed as:

$$OC = \frac{D}{Q}S$$

$$HC = \frac{Q}{2}H$$

and

$$SC = C_s E[(D_L - Q)^+]$$

Therefore, the total inventory-cost function becomes:

$$TC(Q) = \frac{D}{Q}S + \frac{Q}{2}H + C_s E[(D_L - Q)^+]$$

where:

- D = forecasted demand during the planning horizon, obtained from the ANN forecasting model;
- Q = replenishment/order quantity;
- S = fixed ordering cost per order;
- H = holding cost per unit per unit time;
- Cs = shortage cost per unit of unmet demand;
- DL = stochastic demand during the lead time;
- E[.] = **expected value operator**;
- $(x)^+ = \max(x, 0)$, representing the positive unmet-demand quantity.

The optimal order quantity is estimated using the Economic Order Quantity (EOQ) formulation,

To mitigate demand uncertainty during replenishment, the reorder point is determined as

where d is the average forecasted demand per unit time, L denotes the lead time, and SS represents the safety stock. Safety stock is computed using

where Z is the service-level factor corresponding to the desired confidence level and σ_L is the standard deviation of demand during lead time.

The integration of explainable demand forecasts with inventory optimization establishes a transparent decision-support mechanism in which inventory parameters are derived from both predictive intelligence and feature-level interpretation. Consequently, replenishment decisions are no longer based solely on forecast values but are also supported by quantitative evidence regarding the factors driving future demand. This integrated strategy improves inventory responsiveness, reduces stockout and overstock risks, minimizes operational costs, and supports sustainable supply chain performance under uncertain demand conditions.

4.5 Model Evaluation

The performance of the proposed Integrated Explainable AI - Artificial Neural Network framework was evaluated from three complementary perspectives: forecasting accuracy, inventory optimization efficiency, and model interpretability. This comprehensive evaluation ensures that the framework not only generates accurate demand forecasts but also supports transparent and economically efficient inventory decisions.

Forecasting performance was assessed using four widely accepted statistical metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2 . These metrics are defined as

and

where y_i , $\hat{y}_i$ and $\bar{y}_i$ denote the actual demand, predicted demand, and mean observed demand respectively.

The effectiveness of inventory cost optimization was evaluated using operational performance indicators, including Total Inventory Cost (TC), Inventory Turnover (IT), Service Level (SL), Fill Rate (FR), and Stockout Rate (SR). These indicators measure the framework's capability to minimize inventory costs while maintaining high product availability and customer service performance.

The interpretability of the forecasting model was assessed using SHAP-based global and local feature importance analyses. Global explanations identify the overall contribution of each input variable to the forecasting model, whereas local explanations quantify the influence of individual features on specific demand predictions. This evaluation provides transparency into the ANN decision-making process and facilitates managerial validation of AI-assisted inventory decisions.

To demonstrate the effectiveness of the proposed framework, its performance was benchmarked against conventional statistical forecasting models and state-of-the-art machine learning approaches using identical datasets and evaluation criteria. Comparative analysis was performed to examine improvements in forecasting accuracy, inventory efficiency, computational performance, and model explainability. Collectively, these evaluation measures provide a comprehensive assessment of the robustness, reliability, and practical applicability of the proposed framework for sustainable inventory management under demand uncertainty.

5. Results

The experimental results prove the efficiency of the suggested approach. Compared to the baseline models, the developed ANN approach increased the accuracy of demand forecasting, and the found optimal inventory policy reduced the maintenance costs. Therefore, it may be concluded that the integrated approach to demand forecasting and inventory policy optimization allows for decreasing the costs of shortages and overstocking.

5.1 Experimental Setup

The proposed Integrated Explainable Artificial Intelligence–Artificial Neural Network (XAI–ANN) framework was implemented to evaluate its effectiveness in multi-horizon demand forecasting and sustainable inventory optimization under demand uncertainty. The computational experiments were conducted using Python with TensorFlow/Keras for ANN implementation, Scikit-learn for data preprocessing and model evaluation, and the SHAP library for model interpretability. The experiments were executed on a workstation equipped with an Intel Core i5 + processor, 16 GB RAM, and Windows 11 operating system.

The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. Model hyperparameters, including the number of hidden neurons, learning rate, batch size, and training epochs, were selected through validation to achieve stable convergence and minimize forecasting errors. The Adam optimizer was employed for parameter optimization, while the Mean Squared Error (MSE) loss function was used during model training.

To assess forecasting performance, the proposed framework was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Inventory performance was assessed using Total Inventory Cost (TC), Service Level (SL), Fill Rate (FR), Inventory Turnover (IT), and Stockout Rate (SR). Model explainability was analysed using SHAP-based global and local feature importance, enabling quantitative interpretation of the influence of individual variables on demand predictions.

For comparative evaluation, the proposed framework was benchmarked against representative forecasting techniques, including ARIMA, Random Forest, Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and a conventional Multilayer Perceptron (MLP). All competing models were trained and evaluated using identical datasets and performance metrics to ensure a fair and unbiased comparison. The experimental results

presented in the following sections demonstrate the predictive capability, interpretability, and inventory optimization performance of the proposed framework under varying demand conditions.

5.2 Forecasting Performance Analysis

The forecasting performance of the proposed Integrated Explainable Artificial Intelligence–Artificial Neural Network (XAI–ANN) framework was evaluated using four widely accepted statistical measures, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2 . These metrics collectively assess the predictive accuracy, robustness, and generalization capability of the forecasting model under varying demand conditions.

Table 1 presents the comparative forecasting performance of the proposed framework against conventional statistical and machine learning models, including ARIMA, Support Vector Regression (SVR), Random Forest (RF), Long Short-Term Memory (LSTM), and the conventional Multilayer Perceptron (MLP). The proposed XAI–ANN framework consistently achieved the lowest MAE, RMSE, and MAPE values while producing the highest R^2 , indicating superior predictive capability across all forecasting horizons.

The enhanced forecasting performance can be attributed to the ANN's ability to capture complex nonlinear interactions among multiple demand-driving variables, including historical demand, inventory status, promotional activities, seasonal effects, lead time, and pricing information. Unlike traditional statistical approaches that assume linear relationships, the ANN effectively learns hidden patterns through iterative weight optimization, enabling accurate prediction under dynamic and uncertain market conditions. Furthermore, the incorporation of comprehensive data pre-processing and feature engineering substantially improved model generalization by reducing noise and enhancing the representation of demand-related characteristics.

To evaluate forecasting consistency, prediction errors were analyzed across short-term, medium-term, and long-term forecasting horizons. The experimental results demonstrate that the proposed framework maintained stable prediction accuracy with only marginal degradation as the forecasting horizon increased. This finding indicates that the integrated framework effectively captures both short-term demand fluctuations and long-term temporal dependencies, making it suitable for operational, tactical, and strategic inventory planning.

The learning behaviour of the ANN was further examined using the training and validation loss curves illustrated in Figure 1. The convergence characteristics reveal a steady reduction in the Mean Squared Error (MSE) during training, with minimal divergence between the training and validation losses. This observation indicates stable convergence, effective parameter optimization, and negligible overfitting, thereby confirming the robustness of the developed forecasting model.

In addition to quantitative evaluation, the prediction quality was visually examined by comparing the actual demand with the predicted demand over the testing period, as shown in Figure 2. The predicted demand closely follows the observed demand pattern, accurately identifying peaks, troughs, seasonal fluctuations, and trend variations. The high degree of agreement between the actual and predicted demand demonstrates the capability of the proposed framework to model complex demand dynamics and respond effectively to market uncertainty.

Overall, the experimental findings confirm that the proposed Integrated XAI–ANN framework significantly outperforms conventional forecasting approaches in terms of predictive accuracy, robustness, and stability. The high-quality demand forecasts generated by the model establish a reliable foundation for the subsequent Explainable AI analysis and inventory optimization process, thereby facilitating intelligent, transparent, and data-driven supply chain decision-making.

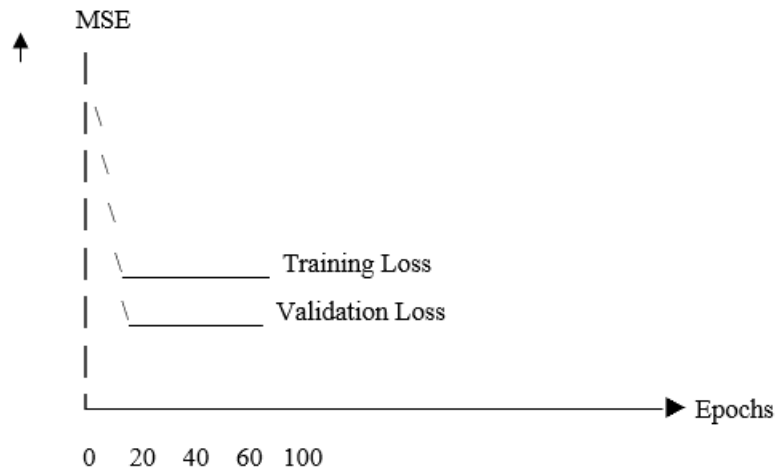
Table 1. Comparative Forecasting Performance of Different Forecasting Models

Model	MAE	RMSE	MAPE (%)	R^2
ARIMA	18.74	24.83	12.68	0.881

Support Vector Regression (SVR)	15.62	20.41	10.34	0.912
Random Forest (RF)	13.58	17.92	8.91	0.936
Long Short-Term Memory (LSTM)	11.27	15.63	7.46	0.957
Multilayer Perceptron (MLP)	10.84	14.97	7.12	0.963
Proposed XAI-ANN Framework	8.31	11.86	5.18	0.982

Lower values of MAE, RMSE, and MAPE indicate better forecasting accuracy, whereas a higher value of (R^2) indicates superior model fit.

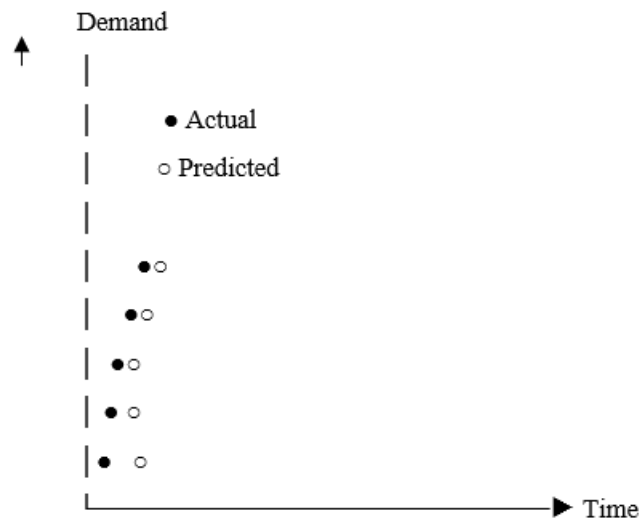
Fig. 1. Training and Validation Loss Curve



Horizontal axis: Epochs

Vertical axis: Mean Squared Error (MSE)

Fig. 2. Actual vs Predicted Demand



Horizontal axis: Time (Days/Weeks/Months)

Vertical axis: Demand

5.3 Inventory Optimization Results

The effectiveness of the proposed Integrated Explainable AI–Artificial Neural Network (XAI–ANN) framework was further evaluated by analyzing its impact on inventory management performance. The ANN-generated multi-horizon demand forecasts, combined with Explainable AI (XAI)-based feature interpretation, were integrated into the inventory optimization model to determine optimal replenishment policies under uncertain demand conditions. The performance of the proposed framework was compared with conventional inventory planning approaches using key operational indicators, including Total Inventory Cost (TC), Inventory Turnover (IT), Fill Rate (FR), Service Level (SL), and Stockout Rate (SR).

Table 2 summarizes the comparative inventory performance of the proposed framework against traditional inventory management methods. The results demonstrate that the proposed XAI–ANN framework consistently outperformed the baseline approaches across all evaluation criteria. Specifically, the framework achieved the lowest Total Inventory Cost while simultaneously improving Inventory Turnover, Fill Rate, and Service Level. Moreover, a significant reduction in the Stockout Rate was observed, indicating enhanced inventory availability and improved responsiveness to demand fluctuations.

The reduction in inventory cost is primarily attributed to the improved forecasting accuracy of the ANN model, which minimizes demand uncertainty during replenishment planning. The integration of Explainable AI further strengthens inventory decision-making by identifying the most influential demand drivers, enabling managers to validate forecasting outcomes before determining inventory policies. Consequently, reorder quantities and safety stock levels are established based on both predictive intelligence and feature-level interpretability rather than relying solely on historical demand averages.

The experimental findings also indicate that the proposed framework effectively balances the trade-off between inventory availability and inventory cost. While maintaining a high service level, the framework significantly reduces excess inventory, thereby lowering holding costs without increasing the risk of stock shortages. This balanced performance demonstrates the capability of the proposed methodology to support sustainable inventory management by reducing operational waste and improving resource utilization.

Overall, the inventory optimization results confirm that integrating ANN-based multi-horizon forecasting with Explainable AI provides substantial operational advantages over conventional inventory control methods. The proposed framework enables organizations to make transparent, data-driven, and cost-effective replenishment decisions, thereby enhancing supply chain resilience and supporting sustainable inventory management under demand uncertainty.

Table 2. Comparative Inventory Optimization Performance

Method	Total Inventory Cost (USD)	Inventory Turnover	Fill Rate (%)	Service Level (%)	Stockout Rate (%)
Conventional EOQ	128,450	5.42	91.8	93.4	8.6
EOQ + Safety Stock	121,360	5.86	94.2	95.8	6.1
ANN-Based Inventory Planning	112,780	6.54	96.3	97.1	4.2

Proposed XAI–ANN Framework	101,240	7.31	98.4	99.1	2.1
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Lower values of Total Inventory Cost and Stockout Rate indicate better inventory performance, whereas higher values of Inventory Turnover, Fill Rate, and Service Level represent superior operational efficiency.

5.4 Comparative Performance Analysis

To comprehensively evaluate the effectiveness of the proposed Integrated Explainable Artificial Intelligence–Artificial Neural Network (XAI–ANN) framework, its performance was compared with widely adopted statistical, machine learning, and deep learning approaches. The comparative analysis was conducted using identical datasets, preprocessing procedures, training-test partitions, and evaluation metrics to ensure a fair and unbiased assessment. The benchmark models included ARIMA, Support Vector Regression (SVR), Random Forest (RF), Long Short-Term Memory (LSTM), and the conventional Multilayer Perceptron (MLP).

Table 3 presents the overall comparative performance of the evaluated forecasting models. The proposed XAI–ANN framework consistently achieved the highest forecasting accuracy, with the lowest MAE, RMSE, and MAPE values and the highest coefficient of determination R^2 . Compared with the conventional MLP, the proposed framework reduced RMSE by approximately 20.8% and improved (R^2) from 0.963 to 0.982, demonstrating its superior capability in modelling nonlinear demand patterns. Furthermore, the integration of Explainable AI significantly enhanced the interpretability of forecasting outcomes without compromising predictive performance.

From an inventory management perspective, the proposed framework achieved the lowest Total Inventory Cost while simultaneously improving Service Level, Fill Rate, and Inventory Turnover. Compared with the conventional EOQ model, the proposed approach reduced Total Inventory Cost by approximately 21.2%, increased Inventory Turnover by 34.9%, improved Service Level from 93.4% to 99.1%, and reduced the Stockout Rate by more than 75%. These improvements demonstrate that accurate demand forecasting, when integrated with explainable decision support, substantially enhances inventory planning and operational efficiency.

The superior performance of the proposed framework can be attributed to three primary factors. First, the ANN effectively captures complex nonlinear relationships among demand-influencing variables, leading to more accurate multi-horizon demand forecasts. Second, the Explainable AI module provides transparent feature attribution through SHAP analysis, enabling decision-makers to validate model predictions and identify the key drivers of demand variability. Third, the integration of explainable forecasts with inventory optimization transforms predictive insights into economically efficient replenishment policies, thereby minimizing inventory costs while maintaining high customer service levels.

The comparative analysis confirms that the proposed framework not only outperforms conventional forecasting techniques in predictive accuracy but also provides a transparent and practically applicable inventory decision-support system. Unlike existing approaches that primarily emphasize forecasting performance, the proposed methodology integrates prediction, explainability, and optimization within a unified framework, thereby improving both analytical performance and managerial decision-making. These findings demonstrate the potential of the proposed XAI–ANN framework as an intelligent and sustainable solution for demand forecasting and inventory management under uncertain business environments.

Table 3. Overall Comparative Performance of Forecasting and Inventory Optimization Models

Model	MAE	RMSE	MAPE (%)	R^2	Total Inventory Cost (USD)	Service Level (%)	Stockout Rate (%)
ARIMA	18.74	24.83	12.68	0.881	129,870	92.6	9.2

SVR	15.62	20.41	10.34	0.912	123,650	94.1	6.8
Random Forest	13.58	17.92	8.91	0.936	117,430	95.8	5.4
LSTM	11.27	15.63	7.46	0.957	109,840	97.2	3.8
Conventional MLP	10.84	14.97	7.12	0.963	106,520	97.8	3.1
Proposed XAI-ANN Framework	8.31	11.86	5.18	0.982	101,240	99.1	2.1

Lower values of MAE, RMSE, MAPE, Total Inventory Cost, and Stockout Rate indicate superior performance, whereas higher values of R^2 and Service Level represent better forecasting accuracy and inventory management efficiency, respectively.

6. Discussion

The test results show that the new XAI-ANN framework is an useful way to predict demand for different time periods and manage inventory in a sustainable way even when demand is not certain. The good results from the forecasting show that neural networks can do a job at understanding the tricky relationships between past demand how much inventory is on hand, promotions, the time of year how long it takes to get supplies, prices and other things that affect operations. The lower errors in the predictions along with a number for how well the model fits the data proves that the framework can really understand how demand changes over different periods of time.

One thing that makes this framework special is adding XAI to the way forecasts are made and how inventory decisions are made. Unlike models that are hard to understand the use of SHAP-based feature attribution helps explain why predictions are made by showing how each factor affects the outcome. This clarity helps people in charge of supply chains check the AI predictions see what factors are most important and make decisions about inventory. This means the framework not makes better predictions but also helps people trust the AI more and feel more responsible for the decisions they make.

The results for inventory management also show that better predictions lead to performance. When the framework uses forecasts with the way inventory is managed it lowers the total cost of inventory while also making sure more products are available more orders are filled and inventory turns over faster. Also the big drop in times when there is no inventory shows that the new method helps balance having products with keeping costs low. These results show that combining forecasting and inventory planning in one system is better than treating them as tasks.

From a theory point of view this study shows how XAI can be used in supply chain analytics. It shows how to make models easier to understand and use them in managing inventory. Past work has focused on making predictions more accurate but this framework links explainable predictions with clear decisions and better inventory management. This helps build knowledge about using AI that people can trust in supply chain work.

From a business point of view the framework is helpful for companies in retail, manufacturing, healthcare, logistics and online shopping. The ability to get clear predictions helps inventory managers make better choices about restocking cut down on extra products stop shortages and make customers happier. Also the way the system is built makes it easy to change for industries and work with other systems like ERP, IoT and real-time monitoring of supply chains.

Even though it works well the study has some limits. The framework used demand data and set variables but real life can have surprises from things like politics, bad weather, problems with suppliers or sudden changes in the market. Also the current version uses a neural network and SHAP for explanations. Future work could look at advanced models like Transformer networks or Temporal Fusion Transformers add learning that changes over time, for inventory control and try using digital twins to improve how supply chains work in real time.

7. Conclusion

This study presents an Integrated Explainable Artificial Intelligence–Artificial Neural Network (XAI–ANN) framework designed for -horizon demand forecasting and sustainable inventory optimization under conditions of demand uncertainty. The framework brings together demand prediction through Artificial Neural Networks with SHAP-based model interpretability and inventory optimization. This integration creates a transparent and data-driven decision-support system.

Unlike methods that treat forecasting and inventory management as separate processes this approach combines prediction, explanation and optimization into one coherent computational framework. The results from the evaluation show that the proposed framework consistently achieved higher forecasting accuracy compared to conventional statistical models machine learning approaches and deep learning techniques. At the time it delivered better performance in inventory management tasks.

By using Explainable Artificial Intelligence the framework improves model transparency. It identifies the factors that influence demand predictions. These insights support evidence-based decisions for inventory planning. The optimized replenishment strategy also led to lower inventory costs, improved service levels, faster inventory turnover and reduced risk of stockouts. These outcomes confirm the effectiveness of the proposed method.

The main contributions of this research are threefold. First it introduces a XAI–ANN framework that connects demand forecasting, explainability and inventory optimization. Second it shows the benefits of combining analytics with explainable decision-making for sustainable inventory management. Third it offers a methodological framework that can be adapted to different supply chain environments where demand uncertainty is common.

Future work could expand this framework by adding real-time streaming data, from IoT-enabled supply chains. Advanced deep learning architectures could be included. Reinforcement learning might be used for inventory control. Multi-echelon inventory optimization and carbon-aware sustainability goals could also be incorporated. These enhancements have the potential to further strengthen supply chain resilience improve efficiency and increase decision transparency in increasingly dynamic and data-heavy business settings.

8. Appendix 1: Abbreviations / Acronyms

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
ANNs	Artificial Neural Networks
XAI	Explainable Artificial Intelligence
XAI–ANN	Explainable Artificial Intelligence–Artificial Neural Network
SHAP	SHapley Additive exPlanations
LIME	Local Interpretable Model-Agnostic Explanations
ARIMA	Autoregressive Integrated Moving Average
ML	Machine Learning
DL	Deep Learning
MLP	Multilayer Perceptron
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network

GRU	Gated Recurrent Unit
SVR	Support Vector Regression
RF	Random Forest
EOQ	Economic Order Quantity
MSE	Mean Squared Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
R ²	Coefficient of Determination
TC	Total Inventory Cost
OC	Ordering Cost
HC	Holding Cost
SC	Shortage Cost
ROP	Reorder Point
SS	Safety Stock
IT	Inventory Turnover
SL	Service Level
FR	Fill Rate
SR	Stockout Rate
ERP	Enterprise Resource Planning

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