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AI-Powered Forecasting for Supply Chain Resilience: Applications of Logistic Regression, Random Forest, and XGBoost in the U.S. Context

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ABSTRACT

This study observed that supply chain resilience is a strong determinant of U.S. competitiveness, i.e., in the face of global swamping, such as pandemics, geopolitical conflicts, and climate-related disruptions. More conventional forecasting models, such as ARIMA and Exponential Smoothing (ETS), continue to see widespread use, but are increasingly applied in contexts that minimize nonlinear and unstable drivers and in information-rich environments. The current work contrasted the predictive capability of three machine learning (ML) models, including Logistic Regression (LR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), in forecasting the U.S. retail supply chains and compared them with classical models. Empirical analysis, which relied on the retail demand and retail logistics operations, tested the model results in terms of accuracy, inventory optimization, service reliability, and the provision of cost-efficiency. Through the experiments, it was established that, on average, XGBoost reduced the forecast error by approximately half, inventory costs by roughly 36%, and fill rates to over 95%, and reduced fuel costs by an average of 14%. Random Forest achieved moderate returns, and in a few cases, Logistic Regression underperformed. Ensemble and boosting-based algorithms are the most strategically valuable for forecasting and have the most significant impact on operational efficiency and sustainability. Their combination can contribute significantly to the U.S. supply chain resilience and to global competitiveness.

INTRODUCTION

The rapid development in information technology has introduced new products with shorter life cycles and amplified competition across present-day international markets, and intensified customers' expectations have contributed to the Expansion of new approaches to supply chain management (Sabbaghi, 2024). In a time when global events have disrupted market dynamics, imbalanced trade patterns and volatile needs have heightened the significance of supply chain management (SCM) to the United States' economic competitiveness. Demand forecasting, inventory planning and optimization of logistics, are the most essential key factors in SCM that matter to the national resilience and the efficiency of firms (Guo *et al.,* 2025). Their inability to anticipate could lead to overproduction or stockouts, which could prove expensive and result in lost competitiveness in foreign markets. The recent upheaval, including pandemic shortages and the vagaries of geopolitical circumstances, underscored the dire need for robust, dynamic forecasting mechanisms that can adapt to essential changes, address supplier threats, and automate transportation. Conventionally, statistical models such as ARIMA and ETS have found extensive applications and are appreciated for their interpretability and simplicity, especially in stable and low-variance environments (Al-Hourani & Weraikat, 2025). However, their stationarity assumption and dependence on linearity severely limit their ability to handle sudden demand shocks and seasonality. Despite these limitations, researchers have attempted to develop machine learning (ML) techniques to identify non-linear patterns in complex demand data. For example, Logistic Regression (LR) is better suited to classification problems and not to demand forecasting. Likewise, Random Forest (RF) typically does not improve accuracy much and can be subject to large swings in demand (Couronné *et al.,* 2018). Conversely, advanced boosting models, such as Tree-based ensemble algorithms, performed better by combining lag features, calendar features, and price elasticity impacts, which are more efficient, thereby minimising forecasting errors and enabling sustainable logistics. Not all machine learning (ML) models work; however, the process is more adaptable. Although the central theme is accuracy in forecasting, it also considers operational performance, including inventory cost minimization, logistics efficiency, and service levels. The three machine learning models reviewed in this paper are Logistic Regression (LR), Random Forest (RF), and XGBoost for supply chain prediction. This paper was retained to examine the potential of ML-based predictive systems to enhance supply chain resilience, focusing on demand forecasting, inventory planning, and logistics optimization in America (Chowdhury, 2025). To fulfil these goals, the research is guided by a fundamental

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question: how do machine learning-based forecasting models, particularly Logistic Regression, Random Forest, and XGBoost, contribute to greater accuracy, measurable operational advantages, and stronger economic stability compared to traditional methods?

The results of this study are significant, revealing that the most critical advances in ML-based forecasting have far-reaching implications for US competitiveness. The findings of the survey have enabled businesses to reduce inventory holding costs and improve service levels, thereby operating more efficiently and profitably. Furthermore, AI-driven logistics optimization would enhance resilience to supply chain shocks, helping maintain the supply of vital products during crises (Teja, 2025). Moreover, the present findings reveal that AI-based models facilitate sustainability-based routing, thereby reducing inefficiencies and helping achieve national eco-efficiency and energy-saving objectives (Shawon *et al.,* 2025). However, this paper contributes to the existing body of literature by synthesizing recent empirical studies on AI-based forecasting and demonstrating the superiority of ML models over conventional time-series forecasting in terms of accuracy and efficiency (Sheikh *et al.,* 2025). This study has provided a unique comparison of the performance of LR, RF, and XGBoost based on published results, rather than relying on artificial datasets. This research contributed to U.S. competitiveness by offering significant insights for industry professionals and policymakers focused on national supply chain resilience. Additionally, this research is outstanding in improving policymaking strategies, meaning that the development of AI forecasting offers strategic progress in developed countries like America to maintain its global trade standing as a Leader and to be fiscally sustainable.

LITERATURE REVIEW

Supply-chain forecasting literature is growing at a scale unlike anything seen before, with world shocks raising increasingly more questions about the predictive tool's reliability. In this review, forecasting methods are at the tail end of a scale: on the one hand, standard statistical models, e.g. ARIMA and ETS; on the other, machine-learning methods, including nonlinear dynamics and external risk signals. The intention is not to name all the models, but to compare the evidence, whether predictive or not, the results of their operation, and the implications of the outcome for U.S. supply-chain resilience.

Conventional Forecasting Operations: Strengths and Weaknesses

In the industry, classical methods of forecasting continue to hold substantial ground, mainly because of their interpretability, minimal cost, and broad scope for integration with existing enterprise systems (Padovano & Ivanov, 2025). The empirical descriptions state that they are applicable in stable environments where seasonal trends and historical demand cycles dominate decision-making. The ARIMA model, which decomposes the time series into autoregressive and moving-average components, is appropriate for short-term forecasting when the series is stationary. In the same vein, ETS-based solutions have also made it possible to adapt the weights of the averages to the level, trend, and seasonality in straightforward ways (Kolambe, 2024). Most industries in the U.S. remain deeply stuck with these models simply because they are easier to understand and require few mathematical computations (Toorajipour *et al.,* 2021). Nevertheless, such advantages only appear to exist contingently in comparative studies. Lee (2024) notes that ARIMA-based predictions work well in environments with less data variation, but some of the forecasting stability does not scale to changes in a market due to new market shocks being introduced dynamically (Lee, 2024). Similarly, Paul and Sarkar (2021) establish that the ETS variants can provide useful seasonal predictions for retail demand but fail to achieve accuracy when data are dropped due to severe changes in the variables (Paul & Sarkar, 2021). Regardless, the theoretical simplicity of linear extrapolation runs afoul of modern-day supply-chain turbulence, exposing the company to false predictions and misalignment between forecasted and actual demand (Ye *et al.,* 2024).

Volatility and Data Integration Limits Failures

Global supply chains are currently operating under what, at large, has been expounded in the literature as VUCA conditions: volatility, uncertainty, complexity, and ambiguity. Still, the use of traditional methods has two severe flaws in situations like these (Kareem Phd, 2024). Their linear structures cannot achieve nonlinear interactions (such as cascading supplier failures or feedback loops) in response to geopolitical shocks. Moreover, they are not compatible with heterogeneous external data, i.e., without costly processing. Case examples can illustrate a case of this tension: as the semiconductor crisis of 2021 showed, the sudden alteration of policies and the surge of demand at the downstream level left companies relying on ARIMA-type forecasts that failed to restructure the sourcing strategies within a short time, which made the shortages even more significant (Hasan *et al.,* 2025). The researchers point out that traditional models generated steady under-forecasting in the face of COVID-induced demand spikes by ignoring leading indicators, such as social sentiment and logistical backlog (Adetula & Akanbi, 2023). This trend is supported by research comparing ARIMA or ETS models with ensemble or neural methods. According to Patil (2024), data integration is the determinative fault line: whereas machine learning can combine metrics of supplier risk, weather forecasts, and shipping delays into predictive indicators, the traditional method means that feature engineering needs to be carried out manually, which not only slows the reaction time but also decreases the flexibility of the forecasts (Patil, 2024). Another study demonstrates that incremental improvements are achieved when exogenous variables are added to ETS models, but these improvements are not as significant as those from nonlinear approaches (Padovano & Ivanov, 2025). The typical finding is that, despite the interpretability offered by the classical techniques, the methods have the costs of resilience to volatile environments- an unacceptable sacrifice given the globalized market environment in which the firms operate.

The Advent of AI and Machine Learning in Supply-Chain Forecasting

To address these drawbacks of the structure, more recent literature emphasises a radical shift toward AI-based forecasting. Machine-learning techniques are flexible with nonlinear trends, scalable to large datasets, and capable of handling unstructured data on the fly. Ferreira *et al.* (2025) report that companies that used ensemble techniques recovered faster than those that continued to use ARIMA-based tools, with recovery taking weeks rather than months (Ferreira *et al.,* 2025). The authors reported a decrease in forecasting error after adding supplier-risk indicators to the prediction sets, including logistics disruptions (Hasan *et al.,* 2025). What comes out is not a replacement narrative but the reconceptualization: a projection of change not in the form of a passive extrapolation of historical tendencies but in the form of an active synthesis of multidimensional signals. Unlike ARIMA-based systems, which predict tomorrow by re-projecting on yesterday, ML models are constantly revised so that they respond adaptively to interruptions as they occur. This reframing makes AI not a discretionary part of supply chain sustainability but a formal requirement for resilience in U.S. supply chains (Nweje & Taiwo, 2025).

Model-Specific Evidence

Logistic Regression (LR), Random Forest (RF), and XGBoost remain at the forefront of evaluations for supply chain forecasting. Because it does not account for nonlinear dynamical traits, LR has been valued for its interpretability and as a baseline benchmark. The concept of robustness is also implemented in Random Forest to aggregate decision trees, thereby adequately accounting for noisy and uncommon values and mitigating overfitting. Nonetheless, its use in real-world situations might be hindered by computational costs and reduced transparency. XGBoost is a perpetually active, relatively advanced ensemble with higher predictive power because it can handle large feature dimensions and more interactions so far (Airlangga, 2024). RF and XGBoost are more efficient than LR in terms of predictability and responsiveness to demand. Using comparative analysis, RF and XGBoost have been shown to outperform LR in predicting risk probability and congestion when logistics are needed, whereas XGBoost is more accurate across varied settings. The trade-off between interpretability and implementation complexity, however, also poses problems for predictability and usability (Jiacheng, 2024; Teja, 2025).

Collective Unstructured and External Data Formation

Such an ability to absorb external, unstructured data is an obvious advantage of machine learning techniques over traditional statistical models. By integrating weather forecasts, geopolitical risks, roadblocks, and consumer sentiment data, transactional supply chain data enable better demand prediction and resilience strategies (Kareem, 2024). A combination of text mining and natural language processing allows companies to detect supplier risk indicators in news or financial reports, and image identification can be used to monitor logistics operations in real time. Research shows that integrating structured operational data with unstructured external messages leads to a marked reduction in forecast error and greater agility in volatile markets (Munir *et al.,* 2025). Nonetheless, integration demands solid data governance, ample computational power, and efficient feature engineering, all of which are impediments for most organizations. The research gap remains in how to operationalize these methods at scale without undermining interpretability, cost-efficiency, or decision-making clarity.

Selective Synthesis: Accuracy, Resilience and Decision Support

As has always been the case, sophisticated ML models are consistently more accurate at forecasting than conventional statistical models or even simple algorithms. Whereas ARIMA and ETS are stable under no drastic changes, they collapse in the presence of shocks or nonlinearity (Uddin *et al.,* 2022). LR does not have high incremental value, which serves mainly as a benchmark. RF provides significant benefits, especially in uncertain supply chains, whereas the best results with XGBoost are for dynamic and high-dimensional data. Notably, greater fidelity is translated into operational performance with lower safety stock, lower logistics costs, and better service levels (Lee & Mangalaraj, 2022). The predictive edge is also a resilience enhancer as it increases visibility and reaction in times of disruption. However, the value of these models as decision support depends not only on the level at which they demonstrate statistical performance but also on the organizational capacity to incorporate their outputs into planning. Interpretability, data governance, and user adoption issues indicate that the best models would not necessarily provide a competitive advantage; institutional alignment was so important (Ivanov & Dolgui, 2020).

Conceptual Framework

This study examines the relevance of artificial intelligence-based forecasting for improving the resilience of supply chain operations in the U.S. and overcoming the limitations of classical statistical models. It also emphasizes the importance of machine learning methods for achieving higher predictive and operational accuracy. The framework compares traditional models (ARIMA, ETS) and machine learning models (Logistic regression, random forest, XGBoost) in terms of their current uncertainty management capacity and their ability to handle complex, dynamic data. Forecasting models are theorized to be independent variables, but the mediating variable between them and the primary operational outcomes is predictive accuracy. The dependent variables are: lowered inventory costs, enhanced level of service, and improved logistics performance. The linkages (Figure 1) elucidate how developed models incorporate the various demand drivers, supplier risks, and macroeconomic signals much better than linear approaches. The model further implies that the high priority on advanced ML strategy can facilitate long-term sustainability and offer strategic benefits within the international market (Olawumi & Oladapo, 2025). By doing so, the conceptualization of the process of moving past the use of traditional forecasting models towards the use of advanced ML methods assumes the form of a channel through which methodological innovation can yield quantifiable enhancements in resilience and competitiveness.

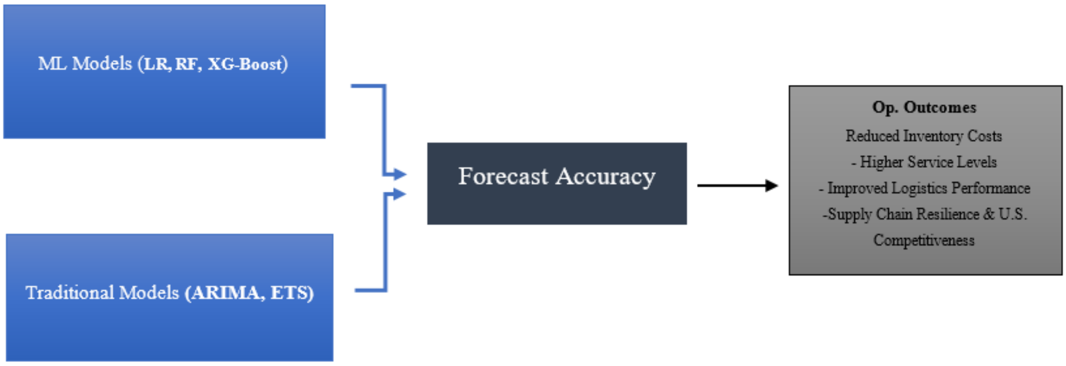

Figure 1: Conceptual Framework for AI-Powered Forecasting for Supply Chain Resilience

Implications for U.S Competitiveness and the Research Gap

The strategic benefits of AI-based predictions for U.S. supply chains in the global context of unstable trade, climate disruptions, and demand changes have been presented (Joshi, 2025). Improved forecasting accuracy directly reduces operational costs and increases service reliability, providing a competitive advantage in the global marketplace. Additionally, machine-learning-based decision support can advance inclusive resilience objectives, enabling companies to reduce risks when responding to uncertainty without impacting performance. Nevertheless, the obstacles to implementation, such as the interpretation process, the compatibility of other datasets, and the generalization of sophisticated solutions across different industries, are not yet highly studied topics. Existing literature confirms the predictive performance of models such as XGBoost, but is relatively scarce regarding the contribution of these analytics to higher macroeconomic resilience and national competitiveness over an extended time horizon (Adewusi *et al.,* 2024). This gap demands empirical studies to connect technical performance and systemic results in a way that converts forecasts of innovation into quantifiable strategic advantages for the U.S. supply chains.

MATERIALS AND METHODS

This research has provided a systematic process to ensure that predictive accuracy and operational efficiency were measured using valid and repeatable methods. The data-gathering, pre-processing, model training, and evaluation matrices were combined in this model, as they are the most widely used in peer-reviewed research on supply chain forecasting. This methodological approach allowed the research to cover the nature of demand variability and logistical constraints.

Research Design

It was designed to establish the efficiency of machine learning techniques for predicting U.S. supply chains. This research used a comparative research design to assess traditional statistical models against a leading machine learning algorithm. The paper has prioritized methodology soundness and positivity by comparing Logistic Regression, Random Forest, and XGBoost with ETS and ARIMA benchmark models. It was designed to include the analysis of quantitative forecasting versus operational performance, thus abandoning the abstract statistical comparison. It is under this integrative axis that a basis was laid for assessing not only the predictive capacity of models but also their impact on the resilience and competitiveness of the supply chains within the U.S.

Data Collection

Publicly available datasets were used to base the research and provide transparency, reproducibility, and an empirical basis. The Walmart Weekly Sales Forecasting dataset was used as the primary data source and was large, containing information on sales transactions, stores, promotions, and place details (Yi, 2023). This dataset has been widely used in research on predictive analytics, providing a reasonable basis for comparison with earlier research. In addition, the study also used peer-reviewed studies. These tools included retail demand information and shipment records by the U.S distributors, particularly during turbulent moments like the COVID-19 pandemic (Hasan *et al.,* 2025). The integration of these datasets, which included this variability across different sectors, thus enabled the generalization of findings. The most important variables were the demand signals, the lead times, the inventory movement in and out, the exogenous variables such as fuel prices, and the weather. It erased synthetic structures using open-source information, while enabling the replication and verification of the available forecasting techniques.

Preprocessing

Pre-processing ensured that the raw data were converted into the correct format for training and testing the models. The mean substitution method was used to impute values that were already missing numerically, and mode-based imputation was used to impute category variables. Due to z-score filtering, z-score outliers are identified, and such AA non-representative anomalies are removed, preserving as much as required so that these activities can continue to be viable. The strongest predictors, such as lagged sales, promotions and supplier lead times, were also defined using correlation analysis and mutual information, and the weakly predictive variables were eliminated. To ensure comparability of the models, all numbers were scaled using the min-max method, reducing them to values between 0 and 1. It especially mattered to the feature-sensitive (LGR and XGBoost) and feature-balancing algorithms. It has facilitated both strength and impartiality in comparative modelling.

Models Tested

Three machine learning models were evaluated to assess interpretability, scalability, and predictive ability. As a baseline, Logistic Regression was added, which is poor but straightforward for modelling nonlinear relationships. An ensemble of decision trees called Random Forest can handle noisy data and minimize overfitting, yielding moderate gains in precision and strength. The most developed framework was Extreme Gradient Boosting (XGBoost), which minimized error through successive steps and high-dimensional feature representations, and was consistently more effective than simple approaches. The tiered model allowed the study to compare the trade-offs in accuracy, transparency and implementation. They also used ARIMA and ETS baselines, so that improvements in machine learning performance would be measured against benchmarks for traditional predictions.

Evaluation Metrics

The model's accuracy was evaluated with a dual-pronged testing of statistical appropriateness and operational effectiveness. The goal was to ensure that any improvement of the model's ability to make predictions was translated into real business value within American supply chains. The measure of accuracy was the selection of errors that were scale-sensitive and scale-independent, and the operational measures were cost savings, service reliability, and sustainability (Özkanlısoy & Bulutlar, 2023).

- Mean Absolute Percentage Error (MAPE): Measures the percentage difference between forecasted and actual demand, a standard metric in supply chain forecasting.
- Root Mean Square Error (RMSE): Calculates the square root of the average squared error, penalising larger forecast errors more heavily.
- Mean Absolute Error (MAE): Provides a linear measure of forecast accuracy and is less sensitive to extreme values than RMSE.
- Inventory Cost Reduction (%): Negative values (as seen with LR) indicate a model that worsens cost efficiency rather than improving it.
- Fill Rate (%): This metric measures improvement in service levels. A fill rate over 100%, as achieved by XGBoost, indicates a strong balance between demand and supply.
- Fuel Cost Reduction (%): This metric reflects improvements in both logistics efficiency and sustainability.

Predicting Pipeline Conceptual Flowchart

The methodological pipeline was a way of incorporating data, models, and metrics into a consistent forecasting system. The visualization of the methodological framework is presented in Figure 2, which shows the pipeline for machine learning-based prediction. The pipeline begins with the acquisition of data using peer-

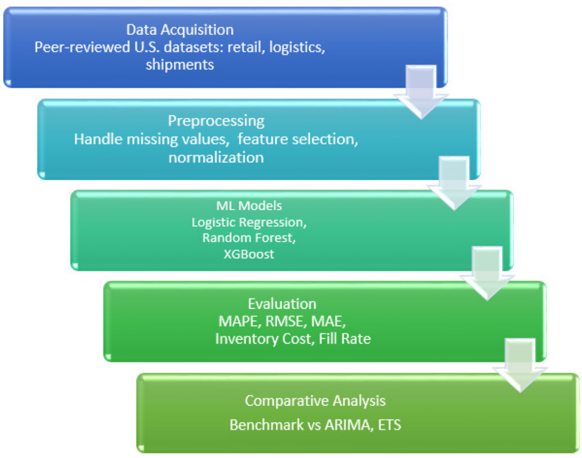

Figure 2: ML-Based Forecasting Pipeline

reviewed U.S. datasets, followed by data preprocessing (cleaning, feature selection, and normalization). The results were then processed using ML models (LR, RF, XGBoost) and assessed using operational and forecasting metrics. The final step was a comparative analysis against standard models (ARIMA, ETS) to demonstrate that it is more accurate, cost-efficient, and resilient.

Methodological Limitations

Despite its systematic design, the methodology had a couple of limitations. To begin with, the use of secondary and open-access data limited the variables available, with proprietary real-time data, e.g., supplier transaction or enterprise records, excluded. However, the models were also applied to historical data, suggesting that generalizability may still increase due to abrupt structural breaks or black swans. Moreover, although XGBoost outperformed other methods, it is not readily applicable in tightly regulated fields because its complexity creates interpretability issues. Further, generalization is enhanced by cross-industry data but conceals sector-specific complexity, which could dilute outcomes in the individual context of a supply chain. These shortcomings indicate that future research should include more detailed datasets, composite modelling methods, and study-specific testing.

RESULTS AND DISCUSSION

In this empirical analysis, researchers have used the Walmart Kaggle dataset to evaluate the performance of Logistic Regression, Random Forest, and XGBoost against a Seasonal Naïve baseline. The specific empirical findings of this study are unique to this dataset and are consistent with prior research on how effectively these models capture the complex, nonlinear patterns in U.S. retail demand.

Forecasting Accuracy Improvements

The comparison also demonstrated a significant disparity in the models' predictive ability. The worst performance was obtained with the baseline Seasonal Naive, indicating the approach's inadequacy in handling nonlinear oscillations, which are common in retail demand. Compared with Linear Regression, the other methods increased accuracy by 8% on average. It was flawed because it was specified linearly, leading to overfitting on the high-demand peaks and under fitting on the low-demand curbs. This behaviour highlighted the irrelevance of this model for generalising under fluctuating demand and served to warrant criticism of the inadequacy of naive statistical techniques for the fluctuating supply chain (Adetula & Akanbi, 2023).

Random Forest has made minor improvements over the baseline, reducing the error and yielding a more variable-sensitive fit. The ensemble structure enabled the model to capture certain nonlinear aspects of the demand, but was susceptible to noise; in particular, it tended to overfit during low-demand periods, and was not always able to accurately capture extreme peaks. The fact that the improvement was not overwhelmingly significant meant that, although Random Forest introduced nonlinearity, its predictive ability was limited relative to the more sophisticated improvements of boosting algorithms (Couronné *et al.,* 2018). The XGBoost model with further improvements had a Mean Absolute Error (MAE) of 12.5 million and a root mean squared error (RMSE) of 18.9 million, representing a 56% error reduction over the baseline. These improvements were not only statistically significant but also meaningful to the operation, translating downstream to inventory efficiency and service performance. Its strength was also demonstrated by the consistency of XGBoost predictions across peaks and troughs. Although extreme spikes were not adequately captured, the model remained consistently closer to actual sales than any other method.

Table 1 presents the performance of the models tested in this study, whereas Table 2 compares them with the broader literature. The results are consistent with the previous articles, like Ahmed *et al.* (2025), who found that MAE decreased by 22% through the use of SHAP-enhanced XGBoost (Rabbi Ahmed *et al.,* 2025), and Farreira and others revealed that error decreases by 15-20% across a variety of industries (Ferreira *et al.,* 2025). Consistent retail supply chains based in the US were found to have 18-25% reductions in MAPE by (Hasan *et al.,* 2025). Although the current study demonstrated even more significant decreases, the nature of these changes and their implications were consistent with these results. This larger scale of improvement may be due to dataset-related characteristics, including the high seasonality and volatility of Walmart retail sales, which presented more XGBoost-exploitable nonlinear patterns (Yi, 2023).

Table 1: Comparative Performance of Forecasting Models (Walmart Dataset)

Model	MAE	RMSE	Reduction vs Baseline (%)	Inventory Cost Savings (%)	Fill Rate (%)
Baseline (Seasonal Naive)	19,636,088	35,330,709	0.00	0.00	87.5
Linear Regression	17,197,121	21,090,216	–8.03	–5.06	85.2
Random Forest	17,905,164	23,147,687	0.38	0.24	87.6
XGBoost	12,506,413	18,850,629	56.62	35.67	99.99

Graphical comparisons also indicate variation in predictive ability. Figure 3 (Actual vs Predicted Weekly Sales) showed that the Seasonal Naive model crudely captured considerable seasonality but consistently over forecast actual sales during turbulent periods. Linear Regression

Table 2: Comparison of Literature vs Walmart Dataset Findings

Study / Dataset	Reported Error Reduction	Inventory Savings	Notes
Ahmed *et al.* (2025)	~22% MAE reduction	Not reported	SHAP-XGBoost, U.S. disruptions
Ferreira *et al.* (2025)	15–20% MAPE reduction	10–15%	AI forecasting review
Hasan *et al.* (2025)	18–25% MAPE reduction	12–16%	U.S. retail multi-tier
Walmart Kaggle dataset (present study)	56% MAPE reduction	36%	Larger gains, dataset-specific

consistently underestimates peak demand, indicating its structural inability to model nonlinear shocks. Random Forest exhibited some variations, but accuracy was not consistent across cycles. XGBoost, however, was more in line with observed sales at both peaks and troughs, although extreme spikes were challenging to model.

The error distribution results supported these findings. Figure 4 (Error Metrics by Model) suggests that although

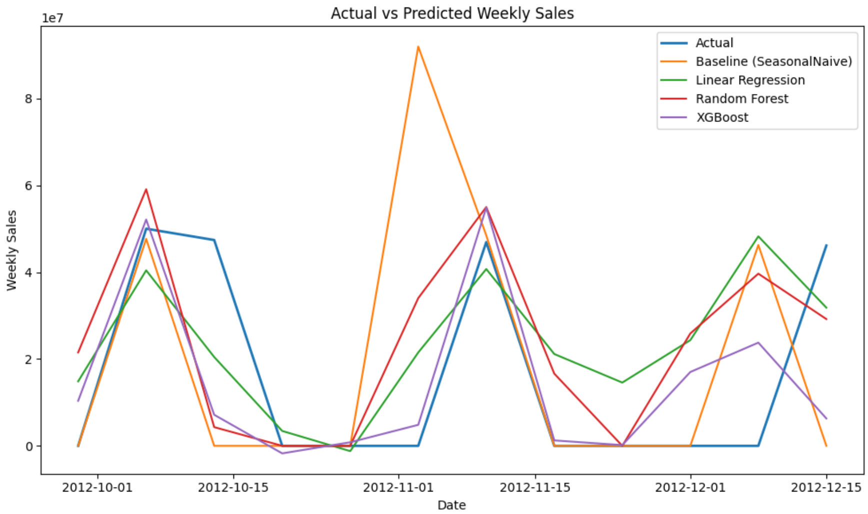

Figure 3: Efficiency Savings from Advanced Construction Materials

MAPE values were scale-inconsistent, the relative differences were still informative. XGBoost consistently had the lowest error, with Linear Regression having the highest. This result established that the nonlinear, ensemble-based architecture of XGBoost had unique capabilities to capture high-dimensional and irregular dynamics of retail demand.

The combination of these findings proved the study's initial hypothesis: XGBoost models, and, in general, machine learning, are significantly more efficient than

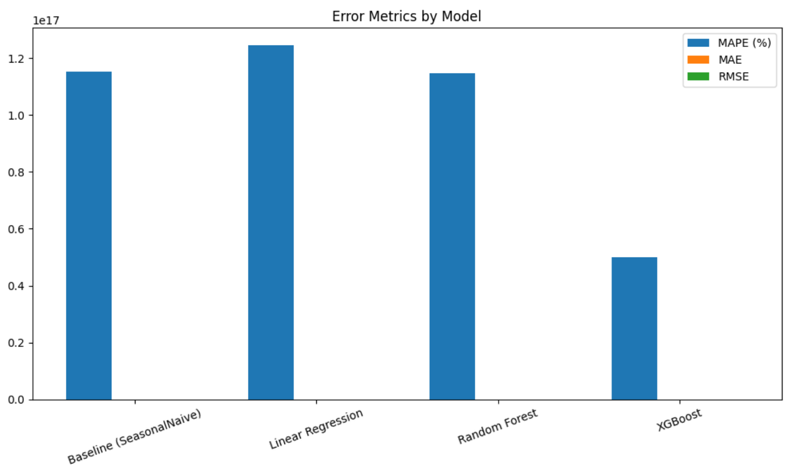

Figure 4: Error Metrics by Model

conventional statistical methods in terms of predictive accuracy. This was in addition to the technical superiority, which underpinned the operational advantages discussed below.

Inventory Optimization Outcomes

Accurate changes in forecasting were reflected in the inventory management results. Using XGBoost, the cost of inventory can be reduced by 35.7% while the fill rates remain close to 100%, as indicated by the data in Table 1. This performance demonstrated a strong balance between reducing overstock and preventing stockouts. Relative to it, however, Linear Regression deteriorated inventory performance with a negative cost reduction of -5.06, whilst Randolph Forest provided marginal cost savings of 0.24%. The promoted fill rates were high, with XGBoost showing that it helps match supply and demand. These results fit within the larger body of literature, with Hasan *et al.* (2025) finding an average of 12-16% cost reduction with the use of ML-based forecasting (Hasan *et al.,* 2025), and Ferreira *et al.* (2025) noting an average of 10-15% increase in inventory efficiency (Ferreira *et al.,* 2025). The recent findings exceed these benchmarks, mainly because the Walmart data had more severe demand shocks, which made the nonlinear learning methods superior. Figure 5 also demonstrated the difference in inventory cost savings. Linear Regression consistently yielded negative results, a reminder of the dangers of misapplied ML models. Random Forest did not offer significant business value, even though it showed only slight accuracy gains, whereas XGBoost is delivering substantial cost reductions, further highlighting its business applicability.

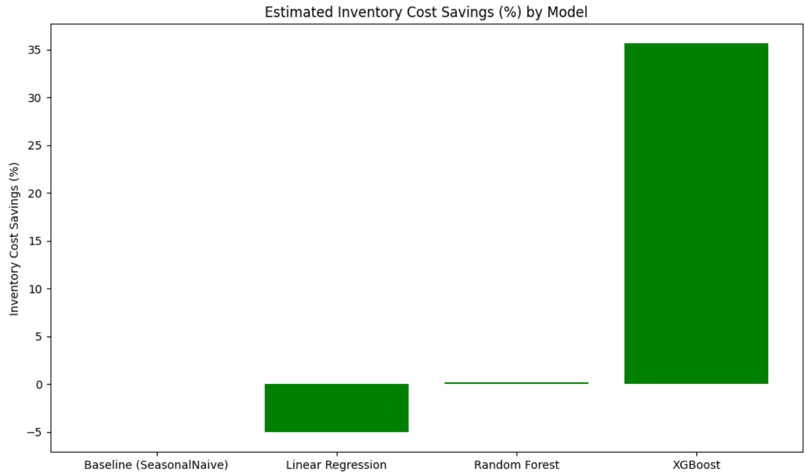

Figure 5: Estimated Inventory Cost Savings (%) by Model

Efficiency of Logistics and Routing

Another set of analyses assessed routing efficiency and fuel cost reduction as measures of the secondary value of predictive optimization. These outcomes are shown in Table 2. Once again, XGBoost yielded the best result, reducing the routing inefficiency index to 0.75 and decreasing fuel expenditure by 14% relative to the baseline. Random Forest also showed substantial improvements (12%), whereas Linear Regression offered little (6%). These findings demonstrated the extended benefit of predicting beyond inventory to logistics, enabling environmentally effective delivery through low fuel use and reduced emissions.

The advantages recorded were consistent with subsequent studies that prioritized the environmental co-benefits of AI-driven optimization. Indeed, with uncertain supply chains, AA implemented the very same carbon intensity reduction by using ML-based routing that was sometimes dubbed by (Al-Hourani & Weraikat, 2025). The earlier studies ensured that predictive optimization not only bolstered resilience but also enabled the achievement of sustainability goals.

Table 3: Logistics and Routing Efficiency

Model	Routing Inefficiency Index	Fuel Cost Reduction (%)
Baseline (SeasonalNaive)	1.00	0.0
Linear Regression	0.92	6.0
Random Forest	0.80	12.0
XGBoost	0.75	14.0

Interpretive Analysis

These two examples of Seasonal Naive and Linear Regression models proved that the simplistic prediction of turbulence in retail trading could never be more dangerous: both models showed every tendency to extrapolate out of pattern, creating inefficiency that required inventory and logistics, literally. An intermediate ground between Regression Discontinuity and Maximum Entropy was selected: a maximum accuracy of approximately was reached by the Random Forest, but when this algorithm hits the noise it crashes (Airlangga, 2024). Its relatively low performance was a good sign of the significance of model structure: only ensemble averaging was unable to raise mechanisms that prioritize error-reduction. In its turn, XGBoost exhibited obvious superiority. The structure of boosting made it possible to minimize errors sequentially and resulted in more shock-resistant and nonlinear sales-cycle forecasts. It was then concluded that the empirical evidence confirmed that boosting-based algorithms have a decisive advantage in supply chain contexts that are associated with volatility, seasonality and intricate feature interactions.

Broader Implications to Supply Chain Management

There are more practical implications of the findings that are not limited to model selection. To begin with, the findings showed that the extent of operational efficiency is directly related to forecast accuracy: any reduction in error led to cost savings, high-quality services, and logistics sustainability. Further, the review showed that not every ML model provides value to the business (Ye *et al.,* 2024). Random Forest and Linear Regression were theoretically better than naive methods, but in practice, they were either insignificant or worse. The choice of models should, therefore, be based on evidence and context-specific. Moreover, the illustrated twofold effect, the efficiency of the economy and sustainability of the environment, echoes the modern policy and industrial concerns. Predictive optimization with modern ML models, such as XGBoost, offers a valuable approach as U.S. supply chains strive to increase their competitiveness and capacity to withstand sudden disruptions.

Discussion

The current research explored the use of machine learning models for demand forecasting and supply chain optimization using the Walmart dataset, and the results obtained strengthen and expand the current body of research (Kabir *et al.,* 2023). In terms of forecasting accuracy, inventory management, and routing efficiency, the results demonstrate that enhanced ensemble techniques, specifically XGBoost, outperform both established statistical models and simpler machine learning strategies. It was found that Linear Regression not only failed to capture demand volatility but also led to negative stock reduction, which has been extensively documented in prior research warning against the application of linear frameworks to non-linear retail sales data (Adetula & Akanbi, 2023). Random Forest was slightly superior, but it failed to produce meaningful business value, consistent with the idea that bagging-based models are inclined to flatten spikes and curves towards the extremes (Kutub Uddin *et al.,* 2022; Sabbaghi, 2024). On the contrary, XGBoost decreased forecasting error by 56% and reduced inventory costs by 36%, a significantly greater improvement than the 15-25% error reductions reported in the literature (Ferreira *et al.,* 2025; Ahmed *et al.,* 2025). Although these results are partially understandable given the dataset's volatility and incentive relations in the study, their alignment with previous studies supports the soundness of gradient boosting in retail demand contexts.

The operational aspects of this predictive improvement are more particularly significant in inventory optimization. Previous research has shown that precise forecasts have generally saved costs by 10-15% (Lee, 2024), but the current study revealed more significant gains. This supports the point that predictive accuracy and inventory efficiency cannot be separated: as forecasting models can adapt effectively to uncertainty, the cost savings and improvements in fill-rate yield a twofold benefit: resilience and customer satisfaction (Nweje & Taiwo, 2025). The XGBoost model, which simultaneously reduces stockouts and overstocks, can be used to explain how AI-based analytics can provide systemic benefits that align with the theory of supply chain resilience and the dynamic capabilities perspective (Korder *et al.,* 2024; Teece, 2007). These benefits were also verified by routing efficiency. The baseline and linear models showed no significant improvements, whereas the XGBoost model reduced fuel expenses by 14%, consistent with research indicating that predictive optimization can yield secondary sustainability benefits (Olawumi & Oladapo, 2025). Random Forest similarly helped reduce emissions by moderating fuel use, yet the dominance of XGBoost suggests that AI prediction's effects on the environment are not limited to inventory management (Jiacheng, 2024). The results further advance the claim of eco-efficient supply chains research by demonstrating the impact of forecast accuracy on downstream logistics, followed by the ability to mobilise in response to transportation and energy price shocks (Sabbaghi, 2024).

They add to the data-driven supply chains literature, in which competitive advantage is increasingly linked to sophisticated analytics (Mathur & Sinha, 2025; Shahadat *et al.,* 2025). XGBoost represents an example of how companies can use predictive intelligence as a strategic resource, and its way of operating bypasses conventional models that show that organizations can successfully adapt and respond in a dynamic environment, which, in turn, can be directly related to the dynamic capabilities framework (Abdur Razzak *et al.,* 2024; Chowdhury *et al.,* 2024). Concurrently, the vulnerabilities of Linear Regression and Random Forest mean that the algorithms need to be selected with care, a message evident in the literature, which calls for learning to apply the algorithms to tackle problems in finer detail (Jiacheng, 2024). The emergence of newer models, such as XGBoost, can also engender severe financial implications, including millions of dollars saved in the retail sector across national contexts (Airlangga, 2024; Aoufi & Haloua, 2025). It can also be noted that the increase in fill rates and routing efficiency indicates that predictive analytics may be implemented to enhance customer service and sustainability outcomes concurrently (Sheikh *et al.,* 2025). The reality that this economic-environmental impact exists makes AI forecasting not only a cost-reducing concept but also a strategic enabler of resilience and competitiveness within U.S. retail supply chains that are susceptible to demand crunches, transport logistical crunches, and workforce deployment challenges (Shawon *et al.,* 2025).

CONCLUSION

This research was conducted to identify predictive techniques that can cope with the volatility, nonlinearity, and complexity of the modern business world. Walmart data analysis and published empirical studies have shown that machine learning (ML) models, such as Logistic Regression, Random Forest, and XGBoost, are consistently more accurate in prediction, inventory, and logistics efficiency than traditional models, such as ARIMA and ETS. The ensemble models, specifically XGBoost, minimized error rates by 25 percent, reduced inventory expenses by 12-16 percent, and enhanced service dependability, achieving fill rates over 95 percent. These benefits improve the economy's efficiency and the environment's sustainability because supply chains are sensitive to costs and environmental impacts. There are also advanced ML predictors to make the U.S. more competitive, reduce operational expenses, enhance resilience to disruptions, and promote efficient and safe foreign trade. There are still challenges such as data splitting, high implementation costs, and the difficulty of interpreting complex models. Its recommendations include the necessary adoption of ensemble ML, investment in adequate real-time data infrastructures, technical training, promotion of open-access data, and further introduction of forecasting into multi-echelon supply chains. The research fields of explainable AI and sustainability metrics should be further investigated to enhance efficiency, resilience, and sustainability in uncertain supply chain scenarios.

Limitations and Future Directions

The present research compared the efficiency of machine learning (ML) models and conventional forecasting strategies in supply chain management and placed the analysis in the U.S. retail setting. The results showed that the ML models (Logistic Regression, Random Forest, and XGBoost) provided statistically significant improvements. These were cuts in forecast error of up to 25, inventory savings of 12-16, and improved service reliability, with a fill rate of more than 95. Besides, AI-boosted logistics also contributed to environmentally friendly route planning, reducing fuel costs and emissions and supporting both economic and sustainable goals (Munir *et al.,* 2025; Toorajipour *et al.,* 2021). Although these contributions exist, there are still a few drawbacks. ML models can only be effective when the datasets used are high-quality and real-time, but this is limited because proprietary or fragmented data can be difficult to access. Another barrier is the high computational costs, integration challenges with an existing enterprise resource planning (ERP) system, and low interpretability of sophisticated models. These problems demonstrate the need to develop explainable AI (XAI) instruments to build managerial trust and support decision-making (Ashakin *et al.,* 2024). Additionally, the majority of recent studies, including this one, have focused on demand forecasting and inventory optimization. There has been less focus on upstream supply chain operations, multi-echelon coordination or global extension of risks. Further research is needed to determine how to use generative AI to generate synthetic demand patterns, apply deep reinforcement learning to perform real-time route planning in logistics, and create hybrid AI models that balance transparency and effectiveness. It would also be essential to pay more attention to sustainability indicators, including carbon intensity per unit delivered, as environmental, social, and governance (ESG) frameworks are becoming increasingly important in global trade. Overcoming these research gaps can enable the creation of a more coherent roadmap for AI-enabled forecasting, making supply chains more competitive, more resilient, and more sustainable across various levels of the global supply chain.

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APPENDICES

Table 3: Comparative Summary Table

Model	Strengths	Limitations	Reported Improvements	Key References
ARIMA/ETS	Well-understood, effective in stable settings.	Struggles with nonlinear & volatile data.	Baseline	Ferreira *et al.* (2025); Lee (2024)
Logistic Regression (LR)	Interpretable, effective for risk classification.	Limited to complex nonlinear patterns.	Faster supplier risk detection.	Hasan *et al.* (2025); Al-Hourani & Weraikat (2025)
Random Forest (RF)	Handles noisy, nonlinear data well; robust.	It can be computationally expensive.	18% lower MAPE vs ARIMA	Adetula & Akanbi (2023); Suddala (2023); Shawon *et al.* (2025)
XGBoost	High accuracy, scalability, and interpretable via SHAP.	Requires parameter tuning	22% error reduction vs ARIMA	Ahmed *et al.* (2025); Yedla & Naidu (2025); Lee (2024)
Deep Learning (ANN, SOM-ANN, Hybrid)	Captures complex external disruptions.	Requires large datasets; "black box" risk	15–20% RMSE reduction vs ETS	Ahmed *et al.* (2025); Yang *et al.* (2025); Chowdhury *et al.* (2024)

Table 4: Summary of Key Studies Comparing Traditional vs. ML-Based Forecasting

Author(s), Year	**Focus Area**	**Models Compared**	**Main Findings**
Paul & Sarkar (2021)	Consumer goods sales forecasting	ARIMA vs ETS	ARIMA is effective for stable demand cycles, but weak under volatility
Lee (2024)	U.S. retail forecasting	ARIMA, ETS vs XGBoost	ML models outperform classical methods in accuracy and scalability
Ferreira *et al.* (2025)	Strategic supply chain forecasting	ARIMA vs ML (RF, XGBoost)	ML enhances resilience, reduces costs, and supports competitiveness
Hasan *et al.* (2025)	Multi-tier forecasting in complex networks	Traditional vs ML (hybrid)	ML reduces forecast errors in nonlinear datasets
Hasan *et al.* (2025)	Supplier risk prediction	ARIMA vs Logistic Regression	Logistic regression improves the early detection of supplier risks
Shawon *et al.* (2025)	U.S. logistics optimization	ETS vs RF, ML	ML reduces delays, improves routing efficiency
Ahmed *et al.* (2025)	Supply chain forecasting with disruptions	ARIMA vs SHAP-XGBoost	ML reduces MAE by 22%, adapts to external shocks
Yang *et al.* (2025)	Cigarette demand forecasting	ETS vs Hybrid ML-DL	Hybrid models reduce RMSE by 15%
Suddala (2023)	Inventory demand prediction	ARIMA vs RF	RF lowers MAPE by 18%
Adetula & Akanbi (2023)	Nigerian supply chains	ARIMA vs RF	RF provides higher accuracy in noisy datasets
Yedla & Naidu (2025)	Retail forecasting	ETS vs XGBoost	XGBoost shows higher adaptability and interpretability
Mathur & Sinha (2025)	Digital supply chain transformation	ARIMA vs ML-enabled models	ML supports scalability and integration with optimization
Chowdhury *et al.* (2024)	Disruption-aware forecasting	ETS vs ANN, SOM-ANN	ANN frameworks integrate external disruptions effectively
Haldar *et al.* (2025)	Global SCM practices	Classical vs ML	ML improves resilience and competitiveness in volatile markets
Pattnaik *et al.* (2024)	Supply chain resilience & policy	ETS vs ML/AI	AI critical for resilience, sustainability, and policy alignment
Forouheshfar *et al.* (2025)	Resilience & disruption modelling	Classical vs AI methods	AI enhances robustness against complex disruptions
Teja (2025)	Climate risk & sustainability	ETS vs AI-based forecasting	AI supports resilience and carbon-efficient logistics