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Enhancing supply chain efficiency through AI-driven demand forecasting: a comprehensive analysis

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Abstract

Artificial Intelligence (AI) has revolutionized supply chain management, especially in demand forecasting, enabling organizations to optimize inventory, reduce costs, and enhance customer satisfaction. This study explores how AI-driven models, mainly the Prophet forecasting tool, enhance demand forecasting accuracy and improve operational efficiency. By examining real historical demand data, this paper evaluates the performance of the Prophet AI-based model, highlights its main benefits, and addresses its challenges. Results suggest that the Prophet model can effectively handle market fluctuations and shifts in consumer needs, offering practical insights for supply chain experts.

Keywords: artificial intelligence, demand forecasting, supply chain management, prophet forecasting model, operational efficiency

Introduction

Supply chain management (SCM) depends on demand forecasting because it helps organizations predict customer needs while optimizing inventory levels and matching logistics operations to market demand. The protection of operational effectiveness and customer satisfaction depends on precise prediction, which also reduces overstocking and stockouts. The current market conditions, with their high volatility and abundant data, require forecasting methods stronger than traditional approaches, including ARIMA and exponential smoothing. The methods demonstrate weakness when dealing with nonlinear or multidimensional systems and time series that exhibit intermittent or erratic demand patterns (Tulli, 2020; Singh et al., 2024).

The accuracy of forecasts directly affects revenue protection as well as production planning and inventory management, according to Tomar et al. (2024). Accurate forecasts provide organizations with a firmer handle on risk. Managers can prepare for volatility or abrupt changes in demand without being surprised with the help of reliable forecasts (Adhikari et al., 2019). Historical forecasting models are usually a disappointment, however. Such models are neither flexible nor fast enough to meet the needs of new supply chain strategies that are required to thrive in today's fast-paced and networked world environment.

Consider a manufacturer sourcing components from three continents. A sudden shipping delay or policy change can disrupt supply overnight. Older forecasting methods cannot adjust quickly enough, while more adaptive models give the company a chance to respond before the disruption turns into a full-scale crisis. Artificial intelligence (AI) and machine learning models are currently addressing some of the limitations of traditional forecasting methods. The tools demonstrate superior precision, scalability, and responsiveness, which makes them suitable for situations with high uncertainty and changing consumer preferences (Nguyen, 2023; Pal, 2023). AI models use structured and unstructured data from sales transactions, weather data, and social sentiment to generate accurate real-time predictions (Khastgir & Kumar, 2024). This feature extends demand sensing, inventory management, and service level throughout the supply chain.

Empirical evidence supports these claims. AI and hybrid models not only show improved performance over the classical approaches and methods but also lower forecast errors and align the trends in a superior manner (Nguyen, 2023; Pal, 2023; Hasan et al., 2025).

The use of AI also reduces expenditure and makes the supply chain more flexible for organizations, enabling them to handle risks more effectively (Jones, 2025). Additionally, the adoption of AI reduces costs and makes the supply chain more flexible, enabling businesses to manage risks better (Jones, 2025). However, challenges such as data quality and interpretability (or explainability) of AI, and workforce preparedness all need to be addressed successfully in order to maximize the benefit of AI from the demand forecasting context (Aljazzar, 2023).

Research Objectives

We study the performance of demand forecasting by applying the Facebook-developed Prophet model to historical demand data. The ultimate objective is to test the validity, interpretability, and business value of Prophet in realistic supply chain scenarios. Of particular interest in this study are the following:

- Make demand forecasts for the short- and medium-term using the Prophet model from past sales history.
- Evaluate forecast accuracy by comparing predicted vs. actual demand, using confidence intervals and trend alignment.
- Compare the Prophet model with other AI-based models such as XBoost and Random Forest.
- Discuss the business implications of the forecasts, which include their potential for inventory optimization, risk mitigation, and decision support.

Literature review

Traditional Statistics-based methods have long been the underlying techniques for demand forecasting in supply chain planning. However, the latter will face limitations in managing real demand patterns. One of the known challenges lies in their ability to understand and get a stable insight into nonlinear patterns, seasonality, and abrupt market transitions (Hasan et al., 2025). Their dependence on static data assumptions and their inability to account for external influences (e.g., macroeconomic indicators, climate) tend to decrease forecast quality, especially during periods of market instability(Aldahmani et al., 2024).

AI And Machine Learning in Forecasting

Advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies have made demand forecasting more accurate and effective than ever(Sangeetha et al., 2024). Models such as XGBoost and Random Forest have been observed to outperform by dealing with complex, high-dimensional datasets and automatically detecting non-linear relationships (Hasan et al., 2025).

These algorithms perform well by integrating diverse data sources—such as real-time IoT sensor data and unstructured social media indicators—and achieving accuracy rates up to 34.6% higher than traditional techniques (Anchuri, 2024). Their ability to learn and adapt is paramount in supply chains affected by demand volatility. Table 1 provides a comparison between XGBoost and Random Forest:

Table 1. Comparative Analysis – XGBoost vs. Random Forest

Aspect	XGBoost	Random Forest	Citation(s)
Disease Detection	Accuracy: 96.45%	Accuracy: 96.75%	(Tuama, 2025)
Ionospheric Signal Disturbance	Recall: 0.84; lower precision	Recall: 0.53; Precision: 0.488	(Arnaut et al., 2024)
Poverty Prediction (Regression)	Higher MSE & MAPE	Lower MSE & MAPE	(Prastiyo & Febriandirza, 2024)
Rainfall Prediction (Regression)	Slightly higher RMSE	Slightly lower RMSE	(Sharma & Rattan, 2024)
Computational Efficiency	Efficient with large datasets; supports parallelism & regularization	Easier to implement; more interpretable but slower	(Fatima et al., 2023)
Weather Prediction	Lower MAE, MSE; higher R^2	Slightly underperforms compared to XGBoost in weather data handling	(Syahreza et al., 2024)
Vehicle Insurance Interest	Higher recall and AUC-ROC; lower precision	Lower recall; potentially higher precision	(Airlangga, 2024)

The Prophet Forecasting Model

Prophet, created by the Core Data Science team at Facebook, has become an industry-strength model for business forecasting. Its key strengths include:

1. **Seasonality handling**: Prophet is intelligent enough to detect recurring seasonal patterns- either through daily, weekly, or yearly transactions- without requiring manual tweaking. Such functional automation makes it practical for business dealing with complex, time-sensitive data flow (Sulandari et al., 2024).
2. **Interpretability**: Unlike "black box" deep learning models, Prophet offers parameters that are transparent and can be easily understood and manipulated by business users (Ahmad et al., 2024).
3. **Robustness**: The model effectively handles missing data and outliers, making it suitable for real-world business data (Sulandari et al., 2024).

Prophet has shown particular success in retail demand forecasting and energy load prediction. In retail, it accurately models holiday demand spikes (Ahmad et al., 2024), while in energy systems, hybrid Prophet-Neural Network models have outperformed traditional ARIMA approaches by 38% (Sulandari et al., 2025).

Methodology

The Demand Forecasting dataset comprises daily historical demand values extracted from real operational data for a single product over five months, spanning from January 1, 2023, to May 30, 2023. The data consist of 150 observations at the daily level, including a calendar date (ds) and a numerical demand value (y). These values reflect plausible variations commonly observed in consumer demand patterns, such as seasonality, trend shifts, and random noise. While this subset was curated for academic research, it preserves the real-world structure and statistical behavior of demand data, rendering it suitable for practical modeling. To evaluate model performance, we applied three forecasting approaches: Facebook's Prophet (a decomposable time series model that handles trend, seasonality, and holiday effects (Rafferty, 2021)), Random Forest Regressor (an ensemble learning method based on decision trees(Fatima et al., 2023), and XGBoost Regressor (a gradient boosting framework optimized for performance and regularization (Zeng et al., 2025). Each model was trained and tested on the same dataset to ensure comparability. The dataset was preprocessed according to the input requirements of each algorithm. For instance, time-based features (day-of-week, month, lag variables, etc.) were engineered for the tree-based models. The Prophet model, in contrast, was fed the canonical ds and y fields without additional feature engineering. Instead of jumping straight into numbers and graphs, I tried to frame the idea of recurring demand patterns with something familiar—the birthday paradox. Think of it as a mental shortcut, a way to picture how often certain peaks in demand can repeat over surprisingly short stretches of time. This analogy makes it easier to see why some patterns seem to reappear almost by chance.

Once that framing is precise, it becomes easier to compare how different forecasting approaches handle those repetitions. Classic statistical models such as Prophet depend on seasonal decomposition—they decompose the signal into straightforward cycles and trends. Machine learning models like Random Forest and XGBoost, however, go in another direction. They do not depend so much on seasonality; instead, they reveal latent, non-linear connections by allowing features to interact in unexpected ways. With that history in mind, here is an in-depth analysis of the dataset we had worked on:

- **Dates:** The calendar date (format: MM/DD/YYYY).
- **Historical_Demand_Values:** Numeric values represent observed demand and show variability and trends that are useful for forecasting. Table 1 shows a sample dataset used to test the AI-based Prophet model.

Table 2. Sample Data from the Demand Forecasting Dataset

Dates	Historical_Demand_Values
1/1/2023	104.9671
1/2/2023	101.7716
1/3/2023	112.7350
1/4/2023	124.4922
1/5/2023	109.7761
1/6/2023	112.4384

Stages of the Prophet Forecasting Model

The Prophet model is designed for time series analysis, capturing trends, seasonality, and holiday effects. Its forecasting process involves:

1. **Data preparation**: We first process the historical time series data to extract patterns.
2. **Model fitting**: Data has a linear or logistic growth shape, may include seasonality, and holidays.
3. **Parameter tuning**: Parameters like seasonality, holidays, and changepoint detection are tuned to boost the performance of the pipeline in predicting the number of contracts sold, up to a 38 percent reduction of the mean absolute percentage error (MAPE) in some scenarios (Sulandari et al., 2024).
4. **Model Comparison:** after applying the Prophet model, we compared it with two other AI models, namely XGBoost and Random Forest.

Results and Analysis

Figure 1 illustrates the analysis of historical demand data reveals several key insights:

- **Seasonal pattern:** The peaks in May and January refer to seasonal peaks, possibly due to festival seasons or advertising campaigns.
- **Trend analysis:** While total consumption is stable, the fluctuations in the short term show heterogeneity in consumer behavior.
- **Business implications:** The work of inventory control and resource allocation, such as the control of stock quantities in cases of demand peaks or troughs, demands precise forecast models.

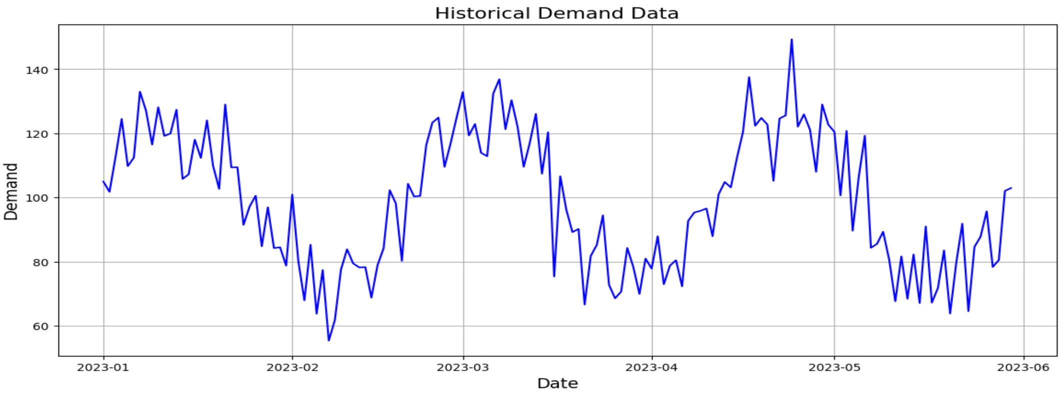

Figure 1. Historical Demand Trends Over Time

By leveraging these demand history patterns, we can now take a look at how good the future forecast by the model (Prophet) is in relation to real values. Prophet is a Facebook open-source forecasting tool that effectively incorporates seasonality, trend changes, and uncertainty in time series data (Sulandari et al., 2024). Figure 2 contrasts actual demand data in the past (black line) with forecasted demand produced by the Prophet model(shaded area). These intervals represent the range of uncertainty associated with future predictions and are derived from patterns in historical fluctuations, seasonality, and potential anomalies in consumer behavior.

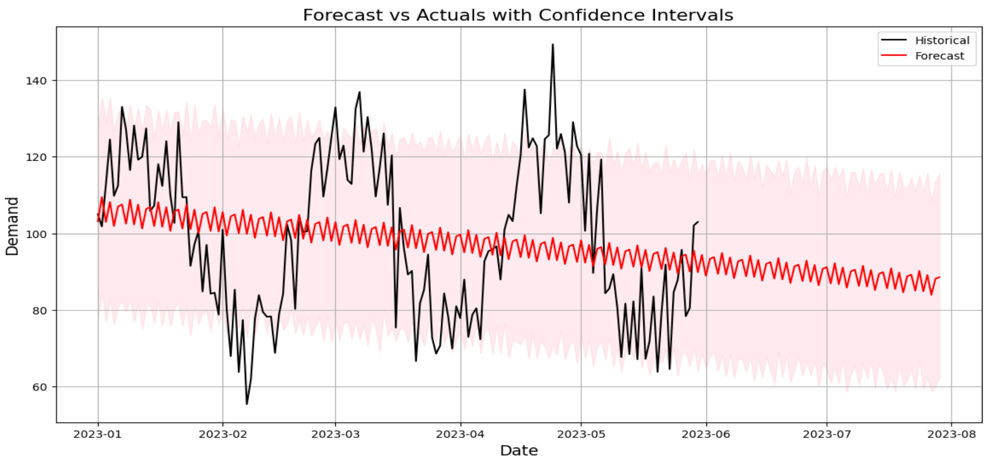

Figure 2. Forecast vs. Actual Visualization

Mean Absolute Percentage Error (MAPE) worked out to 25.52 percent, indicating a moderate difference between the model forecast and the actual results. The Mean Absolute Error (MAE) was 19.75, and the Root Mean Squared Error (RMSE) was 22.81. These results indicate that the model successfully tracked the overall direction of demand but failed in cases involving abrupt changes. A simple example illustrates this well. Imagine a supermarket chain that usually sells a steady number of soft drinks each week. The model can follow that overall pattern with ease. However, if a heatwave arrives unexpectedly, sales may surge overnight. This kind of short-term spike is precisely where the model shows weakness. It recognizes long-term rhythms but stumbles when sharp, unforeseen fluctuations disrupt the trend.

Key Observations:

1. **Trend alignment:** The red line represents the forecast, indicating a downward trend that implies decreasing demand over time.

2. **Historical vs. forecasted data:** The historical time series spreads far more than the 95% confidence intervals, as expected; the model reacts correctly to typical demand changes.
3. **Confidence interval interpretation:** The wide shaded area shows uncertainties, giving a range of possible demand values rather than a definite prediction.

Forecast Accuracy Metrics Table and Analysis

To enhance the performance evaluation of the forecasts, three models, Prophet, XGBoost, and Random Forest, were assessed using standard accuracy metrics: MAE, RMSE, and MAPE. These statistics inform on the scale and spread of the forecasting error, allowing for an unbiased evaluation of the forecasting power of each model.

Table 3. Summarizes the Results

Model	MAE	RMSE	MAPE (%)
Prophet	19.75	22.81	25.52
XGBoost	37.47	41.44	47.66
Random Forest	35.89	39.65	45.64

Prophet scored the lowest errors across all three metrics, indicating that it can effectively model time-series demand data with heavy seasonality and trend effects. In comparison, XGBoost and Random Forest provided greater MAE and MAPE, and were thus less applicable for the cyclical movement of the data in this setting. These findings demonstrate that Prophet is well-suited for demand prediction tasks that rely heavily on historical patterns and seasonal effects. In addition, the interpretable structure and capability to account for uncertainty of the model increase the practical applicability for supply chain purposes. As the MAPE value continues to decrease, the indicative fact is that the Prophet remains the most accurate in the percentage dimension; that is, this is significant when the intention is to measure demand fluctuations at varying degrees of volume control. This empirical validation further supports the case for adopting Prophet in real-world industries with high demands for accurate, timely forecasts that are necessary for operational planning and inventory control.

Business Implications

The composited visualization and forecast accuracy measures support Prophet's capability to model real-world uncertainty and demand variability. In terms of the predictive accuracy (i.e., MAE, RMSE, and MAPE) of our results, Prophet outperforms them, opening a possibility to make decisions for inventory and resource management. Organizations may employ such predictions in:

- Be more confident in predicting changes in demand.
- Reduce the likelihood of overstocking and stockouts.
- Optimize production and logistics planning based on forecast trends

Benefits of Model Comparison

Comparison of models in such a way provides the decision maker with a transparent strategy for choosing a forecasting method. Key benefits include:

- **Trend validation**: Visualization can be used to confirm whether forecast trends are consistent with past trends.
- **Error and bias assessment**: In the forecast metrics/listing and plots, there is an upstream-defined systematic over- or underestimation that may be indicative of model bias.
- **Interpretation of confidence intervals:** Interval shading in Prophet's interval is risk justified: it shows a range of what is plausible.
- **Enlightened planning:** Organizations can more effectively plan resource allocation, manage supplier cycles, and respond to market changes with the application of predictive insight.

Although Prophet was the top-performing model in this work, hybrid techniques that combine Prophet's trend modeling with XGBoost's ability to react to sharp changes could improve the robustness and adaptability of the models in a dynamic supply chain environment.

Discussion

Implications for Supply Chain Decisions

Getting demand right is not simply a technical issue—it is supply chain performance in a nutshell. Where businesses can anticipate what their end-users will demand, they can move forward in confidence. The result? Generally cleaner efficiency, improved resilience, fewer unpleasant shocks (Jones, 2025; Khlie et al., 2024).

AI-powered forecasting tools such as Prophet push this even further. With them, companies can:

- **Tighten stock control.** By reducing both shortages and excess inventory, costs go down while the overall customer experience quietly improves (Khlie et al., 2024).
- **Use resources more carefully.** Foresighting changes in demand allows for limited resources to be used where they are most valuable, reducing waste and friction (Jones, 2025).
- **Keep one step ahead of danger**. Markets are never stable for too long. Managers can make forward-looking, data-based decisions to blunt the effects of disruptions using forecasting models (Jones, 2025).

A fast example illustrates the point. Suppose you are a retailer going into the Christmas season. With forecast models in operation, you are in a stronger position to stock sufficient of the correct products. That results in fewer lost sales and less revenue tied up in stock that does not sell (Amosu et al., 2024). Still, forecasting is not a silver bullet. Businesses need to walk a fine line—balancing profit with trust. Hold too much and you erode margins. Hold too little and you lose customers' confidence. The challenge lies in managing both at once.

Benefits of AI-Driven Models

The application of AI in supply chains, particularly in demand forecasting, has been game-changing. Key advantages include:

- **Improved prediction:** AI models such as Prophet provide the ability to analyze historical data along with external factors in order to make a better forecast. Organizations can anticipate demand variations with this level of accuracy well in advance (Nweje & Taiwo, 2025).
- **Optimized inventory:** AI-infused systems allow inventory management to predict demand since they reduce stocking costs and increase lead time. Through this technique, businesses can maintain sufficient stock levels without over-investing, effectively avoiding over-stocking (Jones, 2025).
- **Better risk management**: AI could allow early identification of potentially disrupting factors (such as supply chain backlogs, or spikes in demand). Beginning with scenario modeling equips organizations with the ability to contend with anything (Grover, 2025).

Practical Recommendations

When companies contemplate the application of AI-based demand forecasting, several realistic steps can separate superficial implementation from fundamental transformation. The steps are not complicated, but they are attention- and discipline-intensive.

- **Enhance data infrastructure.** Good data is the foundation for any AI model. Without correct and reliable information, the most advanced system will not work well. To put it another way, the model will work well if it has been trained on good data. For this reason, the organization must invest in large-scale data collection and data handling processes that allow for reliability and accuracy in the long term (Jones, 2025).

- **Create an innovative culture.** Implementing AI is not merely about new tools but requires a mindset shift. Older work patterns usually resist changes, occasionally subtly. Practically, it implies that organizations need a culture that supports rewarding new attempts and views innovations as a day-to-day activity. Giving training, compensation, and open communication processes can ease the adoption and help lower employee hesitation (Hussain & Rizwan, 2024; Iyelolu et al., 2024).
- **Adopt an incremental approach.** Smaller and medium-sized enterprises, in particular, face constraints on resources. They do not have to embrace the full cost and complexity of AI all at once. A step-by-step method works better. For instance, beginning with pilot projects allows companies to trial ideas, adjust when something does not work as planned, and then scale gradually. This approach minimizes risk while building organizational confidence (Hussain & Rizwan, 2024).

Taken collectively, these steps constitute a larger reality: the addition of AI forecasting tools such as Prophet is not simply a matter of doing everything most efficiently. It changes the nature of the decision-making. It allows companies to be nimbler, to manage costs in a more calculated fashion, and to compete in markets that are, more often than not, unforeseen. To phrase it another way, success will be the domain of those organizations that are leveraging data and resources to react to the future but to forecast it.

Ethical Considerations in AI-Driven Demand Forecasting

With the advent of AI and its application in supply chains (particularly demand forecasting), ethics has come to the forefront. With the progress in digital technologies, privacy, fairness, and transparency are no longer optional but a precondition for responsible deployment and the basis for obtaining and retaining the trust of the various stakeholders.

Data Privacy

Predictive systems that are powered by machine learning do not stand alone. They require vast quantities of consumer and operational data to produce meaningful forecasts. That dependency comes, however, alongside a set of concerns. Gathering and storing the data, along with the procedures used to prepare it, are fairness and accountability issues (Naidu et al., 2024). Rules and regulations exist to reduce the threat of abuse. The General Data Protection Regulation (GDPR), for example, has a clear orientation to the protection of individual privacy. Compliance with such constraints is not optional. Enforcement, if correctly done, safeguards privacy while providing the foundation for responsible data Governance (Sethy et al., 2023).

Transparency and accountability

Another important challenge arises if we consider the manner in which the decisions are reached by machine intelligence. Some models are built from complex, black-box frameworks that even experts do not fully understand. That lack of understanding often prevents the stakeholders from believing in the model or why it made a given prediction (Naidu et al., 2024). Precise algorithms are the inverse and can inspire trust. Decision-makers can more easily look not only at the output but also at the thought process that generated it (Mishra, 2020). Accountability is just as important. Creating clear frameworks for responsibility helps organizations detect and correct unintended consequences, including biases that slip into AI models (MoDastoni, 2023). Ownership and traceability also matter. When models can be tracked and audited, inconsistencies can be investigated, and governance becomes stronger (Gadani & Bhattacharya, 2024). In practice, this means organizations must aim for systems that are not only powerful but explainable. A model that produces accurate results is valuable, but a model that explains itself in a way humans can follow is far more sustainable.

Fairness and Bias
Models built with traditional AI can inherit pre-existing biases even though the model is trained on historical data itself, resulting in biased demand forecasts that discriminate against particular customer segments or regions (Mishra, 2020). For example, there may be an underestimation of demand for a product in historically underrepresented areas due to a lack of representative training data (Yamamura et al., 2022). This risk can be handled by algorithms that have an ethical design, regular model audits, and datasets that are inclusive to showcase the wide range of consumption (Sethy et al., 2016b; Gadani & Bhattacharya, 2024). Although AI offers revolutionary advantages in enhancing the precision and effectiveness of demand forecasting, these benefits must not be achieved at the expense of ethical balance. Careful, proactive attention to these sorts of risks builds trust, improves model quality and performance, and ensures that the benefits of AI are shared fairly among all parties with an interest in the outcome (Purwanto et al., 2024).

Limitations and Future Research

Even in this study, where the author compares Prophet to other forms of AI, such as XGBoost and Random Forest, the analysis does not delve deeply. Consider, for instance, a logistics company that relies equally on the day-of-the-week peaks but also on multi-month seasonal patterns. By pitting Prophet against only two forms of machine learning, the analysis might not show how well each handles the seasonal dynamics. Comparison to a broader group of machine learning and classical statistical models would give a fairer sense of the approaches' relative merits and limitations. Another restriction falls within the dataset itself. The sample has only 150 records, so it does not reflect real-world operation complexity. A store that processes thousands of transactions per day, for example, has volatility that a small dataset will not capture. Besides that, ethical concerns like algorithmic bias or the appropriate use of consumer data were not explored here in detail, though these concerns have considerable gravity in practice (Naidu et al., 2024).

Future work can go in various directions. Increasing the size and diversity of datasets would make results more generalizable. Testing models on other supply chain functions besides the one used here, i.e., procurement, production planning, and even customer relationship management, would reveal the full extent of the value of AI. Of equal importance would be a more in-depth exploration of the ethical and institutional challenges. For instance, suppose a forecasting model accidentally harms small suppliers? Then fairness and transparency will need to be integrated into the design, not as optional add-ons, to ensure fairness. Lastly, longitudinal studies would be precious. They would enable us to observe the impact of AI on supply chain flexibility and sustainability over the course of multiple years rather than at a single point in time.

Conclusion

There are excellent prospects for supply chains in the realm of artificial intelligence. Programs such as Prophet can boost performance, make forecasts easier to interpret, assist in reducing inventory waste, and give companies the ability to react to risks before crises occur. Consider the food distributor preparing for the holidays: by utilizing good forecasts, it can store the appropriate amount of perishables without running out or wasting money. There are problems, naturally. The quality of the data is not always trustworthy, the integration into existing systems is not often straightforward, and the ethics cannot be ignored. The predictive model might predict accurately, but still be problematic if the customer fears the personal data it relies on can be overused. In the future, creating ever-better flexible models and expanding AI's applications in a broader set of areas will be important. The organizations that embrace the possibilities presented by AI in both innovative and the strongest ethical senses will benefit the most. Their supply chains will not merely be operated at lower costs but will also be less vulnerable, more open, and competitive in a world where the one constant is uncertainty.

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References

Adhikari, N. C. D., Domakonda, N., Chandan, C., Gupta, G., Garg, R., Teja, S., ... & Misra, A. (2019). An intelligent approach to demand forecasting. In *International Conference on Computer Networks and Communication Technologies: ICCNCT 2018* (pp. 167–183). Springer Singapore. https://doi.org/10.1007/978-981-10-8681-6_17

Ahmad, A. Y. B., Ali, M., Namdev, A., Meenakshisundaram, K. S., Gupta, A., & Pramanik, S. (2025). A combinatorial deep learning and deep prophet memory neural network method for predicting seasonal product consumption in retail supply chains. In *Essential Information Systems Service Management* (pp. 311–340). IGI Global. https://doi.org/10.4018/979-8-3693-4227-5.ch012

Airlangga, G. (2024). Comparative study of XGBoost, random forest, and logistic regression models for predicting customer interest in vehicle insurance. *Sinkron: Jurnal dan Penelitian Teknik Informatika, 8*(4), 2542–2549. https://doi.org/10.33395/sinkron.v8i4.14194

Aldahmani, E., Alzubi, A., & Iyiola, K. (2024). Demand Forecasting in Supply Chain Using Uni-Regression Deep Approximate Forecasting Model. *Applied Sciences*. https://doi.org/10.3390/app14188110

Aljazzar, S. (2023). *Harnessing Artificial Intelligence for Supply Chain Optimization: Enhanced Demand Prediction and Cost Reduction*. https://doi.org/10.1109/eiceeai60672.2023.10590108

Amosu, O. R., Kumar, P., Ogunsuji, Y. M., Oni, S., & Faworaja, O. (2024). AI-driven demand forecasting: Enhancing inventory management and customer satisfaction. *World Journal of Advanced Research and Reviews*, *23*(2), 100-110.https://doi.org/10.30574/wjarr.2024.23.2.2394

Anchuri, S. (2024). Machine learning-driven demand forecasting: A comparative analysis of advanced techniques and real-time integration. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10 (6). https://doi.org/10.32628/cseit241061175

Arnaut, F., Kolarski, A., & Srécković, V. A. (2024).Comparative Analysis of Random Forest and XGBoost in Classifying Ionospheric Signal Disturbances During Solar Flares. https://doi.org/10.5194/egusphere-egu24-2046

Fatima, S., Hussain, A., Amir, S. B., Ahmed, S. H., & Aslam, S. M. H. (2023). XGBoost and random forest algorithms: an in-depth analysis. *Pakistan Journal of Scientific Research*, *3*(1), 26-31. Link

Fatima, S. S. W., Rahimi, A., & Hayat, K. (2023, August). Comparison of prophet with machine learning regression models for long and short-term manufacturing forecasting. In *2023 28th International Conference on Automation and Computing (ICAC)* (pp. 1-6). IEEE. https://doi.org/10.1109/icac57885.2023.10275201

Gadani, N. N., & Bhattacharya, P. (2025). Ethical Considerations in AI Development for Cloud Computing and Data-Driven Software Solutions. In *Ethical Dimensions of AI Development* (pp. 23-58). IGI Global. https://doi.org/10.4018/979-8-3693-4147-6.ch002

Grover, N. (2025). AI-Enabled Supply Chain Optimization. *International Journal of Advanced Research in Science, Communication and Technology*, 28-44.. https://doi.org/10.48175/ijarsct-23103

Hasan, M. R., Islam, M. R., & Rahman, M. A. (2025). Developing and implementing AI-driven models for demand forecasting in US supply chains: A comprehensive approach to enhancing predictive accuracy. *Edelweiss Applied Science and Technology*, *9*(1), 1045-1068.https://doi.org/10.55214/25768484.v9i1.4308

Hussain, A., & Rizwan, R. (2024). Strategic AI adoption in SMEs: A prescriptive framework [Preprint]. *arXiv*. https://doi.org/10.48550/arxiv.2408.11825

Jones, J. (2025). AI-Driven Demand Forecasting in Supply Chains: A Qualitative Analysis of Adoption and Impact. https://doi.org/10.20944/preprints202501.1349.v1

Khastgir, A., & Kumar, A. (2024). Demand planning: Riding disruptive wave of AI and accelerated computing. International Journal of Supply Chain Management, 13(2), 19–28. https://doi.org/10.59160/ijscm.v13i2.6236

Khlie, K., Benmamoun, Z., Fethallah, W., & Jebbor, I. (2024). Leveraging variational autoencoders and recurrent neural networks for demand forecasting in supply chain management: A case study. *Journal of Infrastructure, Policy and Development*, *8*(8), 6639. https://doi.org/10.24294/jipd.v8i8.6639

Mishra, S. (2020). The Age of Explainable AI: Improving Trust and Transparency in AI Models. *International Journal of Science and Research*, *9*(8), 1603–1611. https://doi.org/10.21275/sr20087120519

MoDastoni, D. A. (2023). Exploring methods to make AI decisions more transparent and understandable for humans. *Advances in Engineering Innovation*, *3*, 32-36.. https://doi.org/10.54254/2977-3903/3/2023037

Naidu, G., Narkhede, U., Shahare, P., Wankhede, P., Deshkar, R., & Gudadhe, A. (2024, November). Ethical Considerations in AI-Driven Supply Chain Management: A Review of Emerging Trends and Challenges. In *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI)* (pp. 1-7). IEEE. https://doi.org/10.1109/idicaiei61867.2024.10842944

Nguyen, T. (2023). Applications of artificial intelligence for demand forecasting. *Operations and Supply Chain Management: An International Journal*, *16*(4), 424-434. https://doi.org/10.31387/oscm0550401

Nweje, U., & Taiwo, M. (2025). Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. *International Journal of Science and Research Archive*, *14*(1), 230-250 https://doi.org/10.30574/ijsra.2025.14.1.0027

Pal, S. (2023). Advancements in AI-enhanced Just-in-Time inventory: elevating demand forecasting accuracy. *International Journal for Research in Applied Science and Engineering Technology*, *11*(11), 282-289.https://doi.org/10.22214/ijraset.2023.56503

Rafferty, G. (2021). Forecasting Time Series Data with Facebook Prophet: Build, improve, and optimize time series forecasting models using the advanced forecasting tool. Packt Publishing Ltd. https://international.scholarvox.com/catalog/book/88911379

Prastiyo, I. W., & Febriandirza, A. (2024). Analisis Perbandingan Prediksi Tingkat Kemiskinan Menggunakan Metode XGBoost dan Random Forest Regression.*Jurnal Media Informatika Budidarma*. https://doi.org/10.30865/mib.v8i3.7892

Purwanto, A. N. I., Fauzan, M., Widya, T., & Azzaky, N. S. (2024). Ethical Implications and Challenges of AI Implementation in Business Operations. *TechComp Innovations: Journal of Computer Science and Technology*, *1*(2), 68-82 https://doi.org/10.70063/techcompinnovations.v1i2.52

Sangeetha, G., Harshavardhan, S. V., Allen Joshua, L., & Anirudh, S. M. (2024). Predictive analysis for supply chain management using extreme gradient boost classifier. *Advanced Research in Science, Communication and Technology (IJARSCT), 4*(4), Article 531. https://doi.org/10.48175/IJARSCT-15987

Sethy, A., Shaik, N., Yadavalli, P. K., & Anandaraj, S. P. (2023). 9 AI: issues, concerns, and ethical considerations. *Toward Artificial General Intelligence: Deep Learning, Neural Networks, Generative AI*, 189-211.https://doi.org/10.1515/9783111323749-009

Sharma, D., & Rattan, P. (2024, November). Rainfall Prediction using Random Forest and XGBoost-A comparative study. In 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI) (pp. 1348-1353). IEEE. https://doi.org/10.1109/icdici62993.2024.10810907

Singh, A. K., Simha, J. B., & Agarwal, R. (2024). Prediction of Intermittent Demand Occurrence using Machine Learning. *EAI Endorsed Transactions on Internet of Things*, *10*. https://doi.org/10.4108/eetiot.5381

Sulandari, W., Yudhanto, Y., Hapsari, R., Wijayanti, M. D., & Pardede, H. F. (2024). Implementation of prophet in American electricity forecasting with and without parameter tuning. Media Statistika, 17(1), 93–104. https://doi.org/10.14710/medstat.17.1.93-104

Sulandari, W., Yudhanto, Y., Zukhronah, E., Slamet, I., Pardede, H. F., Rodrigues, P. C., & Lee, M. H. (2025). Hybrid Prophet-NAR Model for Short-Term Electricity Load Forecasting. *IEEE Access*.https://doi.org/10.1109/access.2025.3526735

Syahreza, A., Ningrum, N. K., & Syahrazy, M. A. (2024). Perbandingan Kinerja Model Prediksi Cuaca: Random Forest, Support Vector Regression, dan XGBoost. *Edumatic: Jurnal Pendidikan Informatika*, *8*(2), 526-534. https://doi.org/10.29408/edumatic.v8i2.27640

Tomar, R. S., & Sharma, A. (2020). Demand forecasting to optimize supply chain management. In *Supply chain management* (pp. 1–13). CRC Press. https://doi.org/10.1201/9781003509561-1

Tulli, S. K. C. (2020). Comparative analysis of traditional and AI-based demand forecasting models.7 (6), 6933-6956 https://doi.org/10.18535/ijetst/v7i6.02

Tuama, M. H. (2025). A Comparative Evaluation of Random Forest and XGBoost Models for Disease Detection Using Medical Indicators.*International Journal of Professional Studies*. Vol 19. https://doi.org/10.37648/ijps.v19i01.002

Yamamura, K., Santana, J. C. C., Masiero, B., Quintanilha, J. A., & Berssaneti, F. T. (2022). Forecasting New Product Demand Using Domain Knowledge and Machine Learning. *Research-Technology Management*, *65*(4), 27–36. https://doi.org/10.1080/08956308.2022.2062553

Zeng, S., Liu, C., Zhang, H., Zhang, B., & Zhao, Y. (2025). Short-Term Load Forecasting in Power Systems Based on the Prophet–BO–XGBoost Model. *Energies*, *18*(2), 227. https://doi.org/10.3390/en18020227