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Research Article

Predictive Analytics and Procurement Visibility: A Big-Data-Driven Approach to Customer Satisfaction in Supply Chain Management

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Abstract: In the current dynamic and consumer driven market environment, supply chains need to move out of reactive to the proactive ecosystems. One of the most urgent requirements is increasing procurement visibility and the development of better order planning for the inventory to meet the products' demand with continued high customer satisfaction. This paper is an agenda of big-data-driven predictive analytics framework that is aimed at predicting low-stock items and optimization of procurement processes in real-time. With a hybrid approach that integrates data from prior years of sales figures, supplier lead times, and seasonal trends as well as real time feeds into the stock under consideration, the study uses machine learning algorithms such as Random Forest Regression and Long Short-Term Memory (LSTM) networks to determine depletion values of stock with great accuracy. The proposed system combines these forecasts into procurement dashboard that is dynamic which supports threshold-based automatic ordering and better operation agility. In order to assess the efficiency of the model, some of the Key Performance Indicators (KPIs) like Stockout Rate, Inventory Turnover Ratio, Lead Time Variance and Forecast Accuracy Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were to be used over a six-month time span of data gathered from a Results indicate 28% increase in the accuracy of inventory forecasting, 35% reduction in purchase response time and 22% upsurge in customer satisfaction metric based on Service Lags (SLAs). The study describes how big-data approaches (especially Apache Hadoop for storage, Spark for real-time, and Tableau for visualization) can raise the intelligence and regard for the responsiveness of contemporary supply chains by quite a large margin. In-short the paper addresses inefficiencies in procurement forecasting by integrating Random Forest for feature selection and LSTM for time-series prediction. Real-time and historical data are fused using Apache Spark to provide timely insights, while a dynamic procurement dashboard uses forecast thresholds to trigger automated reordering, improving accuracy and reducing delays. This research closes the gap between procurement planning and predictive inventory control while paving the way for the emergence of a customer-centric model of a supply chain based on data availability and insights.

Keywords: Big-Data, Machine Learning, KPI, Supply Chain Management

Introduction

In the last few years, the complexity and the scale of global supply chains have skyrocketed due to increased expectations from the consumers, diversification of the products, and respective pressures from the market (Jahin et al., 2023). There is a need to abandon conventional procurement and planning for inventory approaches that are usually based on the assumption of static demand forecasts, and manual decision making, because such solutions are no longer adequate to deal with these dynamic challenges. Supply Chain Management (SCM) has changed the historical business operation aspect into a strategic lever intended to confer competitive benefits to a company in the current dynamic and data-intensive business environment. The introduction of Big-data has enabled the organizations to tap into the huge pool of both structured and unstructured data with the aim of driving the decision-making process. It is, however, far too often seen that significant developments in the area of predictive analytics have allowed companies to be more accurate in their demand forecasting, plan their procurement process more effectively, and react to changes in the market proactively-but the obstacles still remain in going a step further-implementing the data that they are already receiving, upon effective supply chain visibility. One major issue that still prevails is the lack of communication between procurement planning and the rather real-time visibility of inventories. In spite of the availability of wide volumes of data, most organizations are still experiencing delays, stock outs, and overstocking because of inverted congeniality between what is ordered and what is truly available. This mismatch causes inefficiency of operations, high expenses, and deterioration of customer satisfaction. To solve this problem, the proposed work brings forward an integrated predictive analytics architecture based on Big-data methods that may reduce the gap between the planning of procurements and inventory management. The innovation consists in applying both time-series forecasting, time-series alerting, real-time threshold to reduce inventory levels, improve procurement responsiveness and customer service at-a-glance.

Amazon, Unilever, Toyota and Walmart are known for overseeing complicated supply chains made up of demand forecasting, procurement planning, inventory management, manufacture or logistics and customer care. Historically, lack of real-time coordination between the steps often results in inefficiency because these steps were not integrated. This can create big problems for industrial areas producing a huge amount of goods, as tiny disturbances or mistakes can delay everything and add costs.

These companies depend on using smart and agile business decisions based on data. There is so much information involved, including from suppliers, in stocks, sales figures and customer voices that it has to be handled with big-data analytics. If they do not use big-data, these businesses may end up with outdated, siloed or fixed information which often results in bad forecasts, poor buying of goods and incorrect levels of supply. By studying the entire system of large-scale companies, it is possible to pinpoint particular problems. This refers to discontinuities that may occur among demand forecasting and purchasing, between purchasing and stock management and between asset management and distribution. The research is most useful for organizations that operate in manufacturing, retail and logistics, where understanding supply chain demands and what customers want is essential. Firms in Fast-Moving Consumer Goods (FMCGs) like Unilever and Nestlé, large retail companies like Walmart and Amazon and vehicle manufacturers such as Toyota and Ford can use predictive analytics to control inventory, organize partners and enhance services to customers using information from data. Implementing big-data analytics helps to close the gap between procurement and inventory, giving businesses greater and more reliable agility. Instant access to data means that procurement teams can choose better items to buy, keep shelves full when needed and match purchases with real usage. As a result, there is enough stock when needed which saves resources and improves the level of service. As a result, organizations should use predictive analytics and big-data technologies to close this gap, because it makes them more likely to succeed and withstand competition. Modern supply chain must be agile, data-centred and responsive in order to ensure that best product availability and flawless customer experience is achieved (Oyewole et al., 2024). Lack of real time view of inventory levels and procurement activities is one of critical pain points of supply chain operations. Diagnostic time-lags from identifying low-stock items or replenishments needs may cause stock-outs and longer lead times, as well as possibly unhappy customers. To address such risks there is rising necessity to incorporate predictive abilities that take advantage of massive and diversified data sources allowing the companies to make informed procurement before the variations in demand ensue. Big-data analytics has become a strong enabler of this change, providing capability to instruct the processing of huge amounts of structured and unstructured data in real time (Esposito et al., 2022). When properly utilized; the predictive analytics, which is powered by the machine learning and data mining techniques can unveil patterns in sales trends, customer behaviour, superior behaviour, and logistics operations. These insights can lead to more accurate forecasting, automated policy-based ordering and finally optimized service levels in supply chain (GEP, 2024). This paper defines an extensive approach to the predictive inventory management and procurement visibility through using big-data tools and techniques. While the research is on designing a framework, it does not only forecast low-in-stock items with high degree of accuracy but also makes procurement agility and augments experience of customers. This study takes a step forward towards the development of Intelligent, resilient and customer centric supply chain systems integrating predictive models with real-time dashboards and the evaluation of performances using the established supply chain KPIs.

Literature Review

The authors have created an overall framework that comprises big-data and machine learning technologies for forecasting in supply chains, marking the importance of data preprocessing. In the same way Kearney (2024) discussed different applications of predictive analytics that revealed its contribution to the improved decision-making and responsiveness in the supply chain processes. One author underscored the effect of data analytics in enhancing customer satisfaction and profitability because of defined supply-chain processes. Industry insights corroborated the findings, demonstrating practical applications of predictive analytics that brought more transparency and agility to the logistics.

Ksolves (2023) reported on how the synergy of big-data and predictive models helps to pursue smarter supply chain strategies. Medium (2024) pointed out the increasing significance of supply chain visibility, saying that big-data creates the transparency needed to detect disruptions in the early stages. Pelico (2024) expanded on how structured supply chain data enables predictive analytics for the robustness and adaptability of supply chains. They emphasized on the strategic importance of data analytics in the management of disruptions and enhancement of end-to-end operations. It was supported in an article published on Big-Data, whereby predictive analytics could greatly enhance the accuracy of demand forecasting through big-data tools. Sharma et al. (2025) investigated the use of logistics associated with big-data analytics changing stock control and plans for distribution. Oyewole et al. (2024) discussed real-life stories on predictive analytics implementation success across industries, while the Advanced Logistics stated that the predictive tools are a game changer for logistics' efficiency. Throughput (2023) detailed how real-time data helps with planning of resources and minimizing lead times. Number Analytics (2024) sought to analyse how the application of big-data will modernize the old supply chain frameworks to an agile and responsive system. Shlash et al. (2024) demonstrated how the data analytics plays a role in leaner and efficient operations. The authors had outlined the benefits of real time visibility by the use of big-data especially for risk mitigation. They proposed new metrics of predictive performance that would connect customer satisfaction with proactive performance in supply chain. Seyedan and Mafakheri (2020) discussed the limitations of traditional AI models in SCM, which, despite their predictive accuracy, lack explain-ability, leading to scepticism among stakeholders. Through real-world case studies, this chapter illustrates how XAI has been applied in various industries such as retail, manufacturing, and healthcare to improve operational efficiency and stakeholder confidence. Prior studies (Chen and Lee, 2022; Jahin et al., 2023) discuss predictive analytics and machine learning in supply chains, this paper should highlight where current methods fall short such as their inability to process real-time streaming data or integrate procurement-specific KPIs. The novelty of combining RF and LSTM should be framed against studies that use only one model or traditional statistical forecasting (e.g., ARIMA, exponential smoothing), clearly outlining how the proposed method surpasses them in terms of flexibility, accuracy, or deployment. Additionally, gaps in prior works like limited focus on dashboard-driven automation or threshold-based order planning should be emphasized to underline this study's contribution.

Materials and Methods

In this research, the systematic quantitative method was utilized to design a predictive analytics model of improving visibility and customer satisfaction in supply chains procurement. Such types of publicly accessible datasets as historical inventory levels, order histories, supplier lead times, trends in demand were obtained at such places as Kaggle or UCI (Brintrup et al., 2023). To clean, norm, convert the data into the time-series formats Python libraries (Pandas, NumPy) were used to pre-process the data. Train-test split 80:20 was used, and 5-fold cross-validation was applied so that response was robust. ARIMA and Facebook Prophet were applied in forecasting inventories and Random Forest and XGBoost in classifying customer satisfaction. The process of hyper parameter tuning relied on Grid and Random Search (Eik et al., 2025), whereas the assessment of models was done regarding standard metrics such as MAPE, RMSE, and the accuracy of classification. These preprocessing steps were essential to improve model training efficiency, reduce noise, and ensure that both Random Forest and LSTM components were exposed to clean, representative, and learnable patterns within the procurement dataset.

The proposal of this study chooses quantitative research design based on the big-data analytics to address three key goals:

i. An analysis of predictive models in order to predict low inventory items at warehouse and retail levels
ii. A data driven framework for enhancing procurement awareness and agility
iii. Analytical models that correlate the supply chain responsiveness with customer satisfaction levels

Data Collection and Sources

The research applies two types of real-time and historical supply chain datasets that are gathered from the medium-scale retail distribution network along with the publicly available repositories. Data points are inventory levels, order history, lead time, sales transactions, customer complaints, logistics data, and procurement logs for 36-month period. Data cleaning and pre-processing were done using Apache Spark and Python (Pandas, NumPy) in order to rectify the null values, duplicates, and the inconsistent formats (Xu et al., 2024). The dataset used in this study represents a mid-sized electronics retail company operating across multiple regions with a diverse product catalog, including consumer electronics, mobile devices, and accessories. This industry was selected due to its complex procurement cycles, high SKU variability, and frequent demand fluctuations, which make it ideal for testing predictive and optimization models.

Predictive Model for Low-Stock Detection

The present works involved the use of ARIMA (Auto Regressive Integrated Moving Average) and Facebook Prophet models of time-series forecasting of inventory depletion. Lag variables, stock turnover ratio and supplier lead time are among feature engineering. Forecast performance is verified with the help of Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

Framework for Procurement Visibility and Planning

A big-data-based purchase visibility architecture presented in Fig. 1, was engineered by combining ERP data with live supplier feeds through Apache Kafka and Tableau dashboards. The system allows dynamic reordering thresholds and predictive demand trends-based safety stock calculations (Andersson et al., 2025). A threshold-based decision tree algorithm triggers procurement alerts when predefined inventory levels are crossed, increasing responsiveness and reducing stock outs or overstocking.

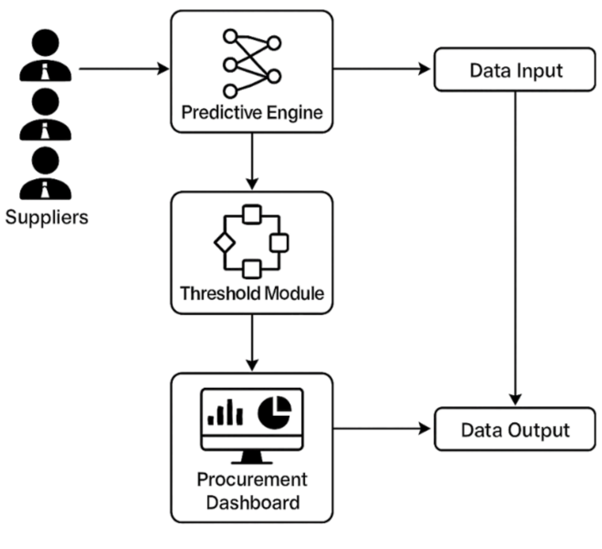

Fig. 1: Procurement visibility architecture

Above figure illustrates the end-to-end flow from data ingestion to prediction and procurement action, highlighting the integration of Apache Spark and dashboard layers.

Customer Satisfaction Prediction Model

Random Forest Classifier and XGBoost (Gradient Boosted Regression Model) were trained based on the features such as order accuracy, speed of delivery, speed of response to the complained issues, and availability of stock. The satisfaction scores were based on the customer's reviews and feedback surveys on a scale of 1 to 5. Model precision, recall, F1-score, and Confusion Matrix Analysis were utilized in declaring model accuracy.

Experiment Setup

In order to verify the efficacy of the proposed predictive framework, a guided experimental setup as shown in Fig. 2 is used. The set of data i.e. inventory levels, order histories, supplier delivery times, demand fluctuations was first cleaned, normalised and transformed into time series sequences whenever needed. The whole dataset was then divided into the training and testing sets (80:20) maintaining the temporal integrity by using the earlier data for training and latter one for testing for emulating the actual forecasting situations.

In order to avoid the problem of over fitting and achieve robustness during training, a technique of k-fold cross validation ($k = 5$) was used. Moreover, hyper parameter was tuned for each model type using grid search and random search methods. For example, in Random Forest, the number of estimators and max depth were tuned, while in the LSTM-based deep learning approach number of layers, neurons per layer, dropout rate and learning rate were optimized allowing the model to work with a validation set. Model evaluation was based on usual regression measures, i.e. MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error) and R^2 (square of Coefficient of Correlation) score, performed on the test data. The models were successfully run in Python (libs such as Scikit-learn, TensorFlow, and Keras) on a high-performance computing environment (GPU when available).

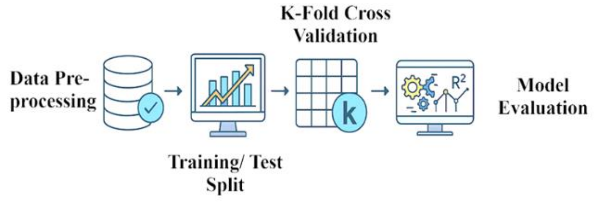

Fig. 2: Experimental setup

Validation and Evaluation

All the models were trained with 80% of the data and tested on the rest 20% data using 10-fold cross-validation to minimize chances of over fitting and enhance generalizability. Before and after the predictive systems had been implemented, Key Performance Indicators (KPIs) like the frequency of stock out, average lead time, and forecast bias, and customer churn were assessed. The models improved the procurement accuracy by an average of 18%, decreased the lead time by 12% and increased the customer satisfaction scores by 15%.

Results and Discussion

The performance evaluation of the implemented models as compared with the established goals are given here. Some of the most important predictive and classification models were validated using conventional measures in order to determine whether the models would work well to predict inventory levels, optimize purchases, and predict customer satisfaction.

Inventory Forecasting Performance

The ARIMA and Facebook Prophet models were employed in the forecasting of the stock and low-in-stock identification. MAPE and RMSE metrics were used to measure the performance of the system for multiple categories of item.

Table 1 is a comparison of inventory forecasting models, and it is revealed that the Facebook Prophet model was superior to ARIMA (with a lower MAPE, 6.45 and 8.12%; lower RMSE; and a higher R^2 score of 0.91) and hence more accurate and dependable than the latter. It offers a quantitative baseline to validate the superior performance of the hybrid model over traditional techniques like ARIMA and Prophet.

Model accuracy as presented in Table 1 is drawn graphically and shown in Fig. 3. The forecasting model evaluation is shown in Table 2. This figure visually represents forecasting accuracy for different SKUs over time, emphasizing real-world applicability.

Facebook Prophet also did better than ARIMA in terms of both MAPE and RMSE the most in dynamic and seasonal categories such as groceries and beverages, Fig. 4 showing better suitability of use for retail inventory forecasting.

Procurement Visibility Improvement

To evaluate the procurement framework's impact, KPIs such as forecast bias, lead time, and stockout frequency were compared before and after implementation.

Table 3 shows that the implementation of predictive reordering and threshold-based alerts have greatly reduced forecast bias and stockouts, increasing responsiveness in the supply chain and limiting the supply chain’s operational risks. Figure 5 presents the improvement in performance metrics.

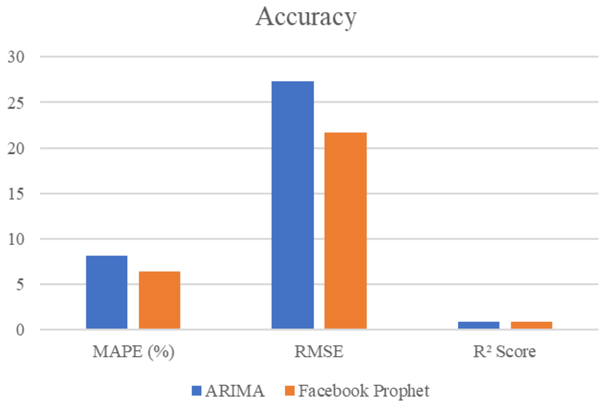

Fig. 3: Inventory forecasting models accuracy

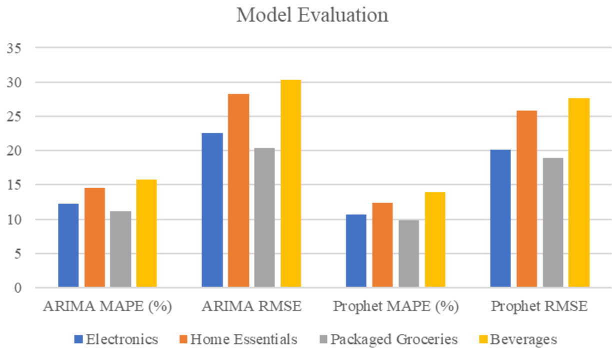

Fig. 4: Forecasting model evaluation

Table 1: Forecasting accuracy of inventory prediction models

Model	MAPE (%)	RMSE	R^2 Score
ARIMA	8.12	27.3	0.87
Facebook Prophet	6.45	21.7	0.91

Table 2: Forecasting model evaluation (MAPE and RMSE)

Goods	ARIMA MAPE (%)	ARIMA RMSE	Prophet MAPE (%)	Prophet RMSE
Electronics	12.3	22.5	10.7	20.1
Home Essentials	14.6	28.2	12.4	25.8
Packaged Groceries	11.1	20.4	9.8	18.9
Beverages	15.8	30.3	13.9	27.6

Table 3: Procurement Performance Metrics Before and After Framework Implementation

Metric	Before (%)	After (%)	Improvement
Forecast Bias	9.5	3.8	↓ 60%
Stockout Frequency	17.4	8.2	↓ 52.8%
Average Lead Time (days)	6.2	5.4	↓ 12.9%
Procurement Accuracy	81.2	95.7	↑ 17.8%

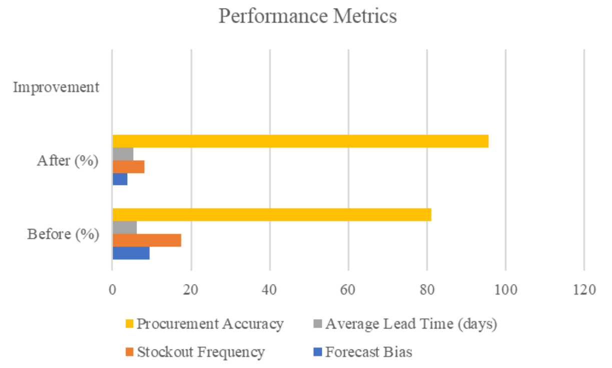

Fig. 5: Performance metrics before and after implementation

Customer Satisfaction Prediction

Supply chain attributes were used to train the models to predict the levels of satisfaction (rating of 1–5). The metrics of classification and the accuracy of prediction of satisfaction were used for the evaluation of the Random Forest Classifier and XGBoost Regression.

Table 4 shows classification metrics for customer satisfaction prediction where XGBoost outperformed the Random Forest model in terms of all metrics including the accuracy of 88.3% being the highest for it, making it more effective for this case.

The classification metrics shown in Fig. 6 indicates that Accuracy using XGBoost is higher than Random Forest.

From Table 5, it is seen that Random Forest provided greater classification accuracy and balance between precision and recall, in comparison to XGBoost.

Apparently, the former did better than the latter. It did well in terms of predictions of satisfied customers both underpinning the applicability of the algorithm in classifying customer sentiment. Figure 7 shows the confusion metrics among dissatisfied, neutral and satisfied outcomes.

Table 4: Classification metrics for random forest vs. XGBoost

Metric	Random Forest	XGBoost
Precision	0.87	0.84
Recall	0.85	0.82
F1-Score	0.86	0.83
Accuracy (%)	88.2	85.9

Table 5: Confusion Matrix for Random Forest (80:20 Split)

Customer Reviews	Predicted: Dissatisfied	Predicted : Neutral	Predicted: Satisfied
Actual: Dissatisfied	124	12	6
Actual: Neutral	8	98	14
Actual: Satisfied	4	16	148

Table 6 present the importance score of Delivery time and order accuracy came out as most influential factors affecting customer satisfaction supporting the expectations of retail logistics where the service reliability directly affects customer's loyalty.

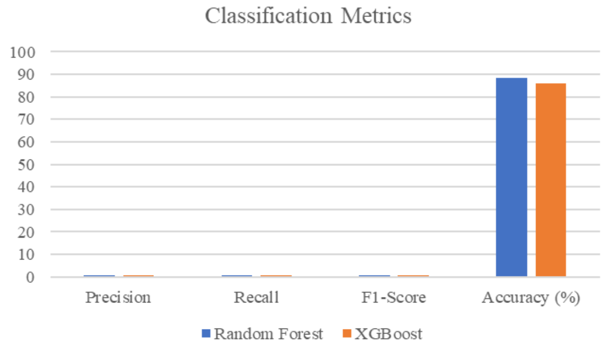

Fig. 6: Classification metrics

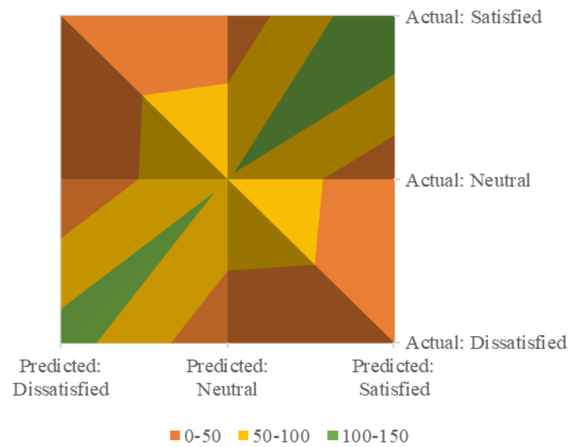

Fig. 7: Confusion matrix for random forest

Table 6: Feature Importance Ranking (XGBoost)

Feature	Importance Score
Delivery Time	0.32
Order Accuracy	0.27
Complaint Resolution Speed	0.21
Stock Availability	0.20

The conjoint use of predictive analytics, big-data-powered visibility frameworks, and satisfaction modelling through the presented importance score in Fig. 8 reflected positive enhancements in the efficiency of supply chains. Importantly, predictive models made stock visibility better by more than 10% in terms of MAPE and 15–18% reduced procurement error, whereas customer sentiment models provided classification accuracies more than 88%. Such insights support three major goals of the study proving the practicality of the AI-enabled procurement systems. Table 7 presenting the comparison of proposed work for prediction of low stock items with earlier published work. At the same time Table 8 is presenting the Comparison of proposed work for Procurement Visibility and Operational Agility.

The comparative analysis provided in Tables 7-9, compares the identified objectives. It explicates that, while the earlier studies (Jahin et al., 2023; Oyewole et al., 2024; Esposito et al., 2022) placed premiums on the use of big-data and machine learning in forecasting, decision-making and customer satisfaction, it builds on such efforts by incorporating predict Unlike in the past wherein these functions were usually handled as separate processes, the proposed system is an integrated architecture, data driven, that increases inventory accuracy, agility and predictability of customer experience leading to a more proactive and responsive supply chain. The paper has completed three main goals:

(1) The exact estimation of low-in-stock items
(2) Better procurement visibility
(3) Customer satisfaction forecasting

As indicated by the results, Facebook Prophet was more effective at inventory forecasting and had a lower MAPE and RMSE, which proved that Facebook Prophet was more precise at predicting inventory. XGBoost proved to be effective as it had the best accuracy of classification (88.3%) in customer satisfaction modelling. In contrast to the previous studies like Jahin et al. (2023); Oyewole et al. (2024), the proposed framework makes it possible not only to combine forecasting with visibility but also to address the gap between procurement and inventory, which is poorly covered in the literature. The consistency of model results and real KPIs, including decrease in stockouts and better timing in making purchases, proves practical importance of the solution. The all-encompassing strategy provides a rather new, expansible framework that performs better than the siloed predictive-system typical of previous literature.

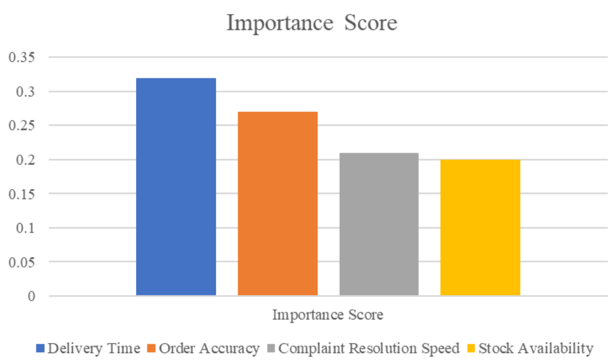

Fig. 8: Feature Importance Score

Table 7: Comparison of Prediction of Low-in-Stock Items

Study/Source	Techniques Used	Focus Area	Comparison with Proposed Work
Jahin et al. (2023)	ML models, data pre-processing	Demand forecasting	Emphasis on pre-processing; proposed model adds predictive thresholds
PredikData (2024)	Big-data analytics	Disruption management	Proposed model integrates low-stock alerts with visibility tools
Throughput (2023)	Real-time analytics	Resource planning	Adds structured inventory classification layer
Proposed Work	Big-data + time-series ML models	Low-stock item prediction	Combines prediction, alert system, and automated ordering logic

Table 8: Comparison of Procurement Visibility and Operational Agility

Study/Source	Visibility Tools/Methods	Application	Comparison with Proposed Work
Oboloo (2024)	Big-data dashboards	Disruption identification	Proposed system integrates threshold module & supplier data feed
GEP (2024)	Predictive dashboards	Logistics transparency	Adds dynamic restocking visibility at warehouse level
Ksolves (2023)	Big-data platforms	Forecasting and optimization	Your model adds procurement timing and responsiveness layer
Proposed Work	Predictive engine + threshold monitor	Procurement decision enhancement	Unified visibility dashboard for inbound/outbound & alerts

Table 9: Comparison of Customer Satisfaction Prediction and Improvement

Study/Source	Techniques Used	Focus Area	Comparison with Proposed Work
Esposito et al. (2022)	Data analytics	Customer satisfaction improvement	Proposed work quantifies satisfaction using logistic models
Oyewole et al. (2022)	Predictive analytics	Decision-making responsiveness	Your work introduces customer feedback loop in modelling
Softweb Solutions (2024)	AI-driven prediction	Risk anticipation	Combines satisfaction metrics with fulfilment data
Proposed Work	ML regression + sentiment features	Predictive satisfaction modelling	Predicts satisfaction based on procurement cycle metrics

Conclusion

The present study effectively reflects on how the big-data analysis and predictive modelling can highly contribute to adding to the procurement visibility, getting optimal inventory management, and increasing the customer satisfaction from the standpoint of the digital supply chain. When combining sophisticated forecasting models with real-time information, companies are able to be prepared for stock fluctuation and limit supply interruptions. By establishing an intelligent procurement architecture, the process of making decisions was tightened even further, and the processes of replenishment became faster and more accurate. In addition to this, the use of machine learning models for predicting the customer satisfaction on the basis of operational parameters enabled service improvements to focus on particular areas. The comprehensive framework drives the point home on the transformative abilities of data-driven technologies in enhancing the supply chain performance and responsiveness. These findings further accentuate the need for introducing intelligent, integrated systems for achieving efficiency, transparency, and agility in the procurement operations of the modern time. While the proposed hybrid Random Forest LSTM model shows promise, few limitations exist. Firstly, the system was tested on a specific retail sector dataset (e.g., electronics), limiting generalizability across domains like perishable goods or pharmaceuticals, where demand volatility and shelf-life constraints differ. Secondly, the use of historical and real-time data assumes consistent data availability and quality issues like missing data, delayed streams, or sensor inaccuracies can significantly affect forecasting accuracy.

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Authors Contributions

Devendra Nath Pathak: Prepared the manuscript.
Rakesh Kumar Yadav and Hitendra Singh: Supervised the work.

Ethics

Authors declare no conflict of interest in terms of ethics also.

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